Second-Best Amendment: Market Power and Tax Design in the Firearms Industry*

Click Here for Latest Version

Luis Armona†, Adam M. Rosenberg‡

February 15, 2026

Abstract

This paper studies the roles of market power and taxes in determining market surplus and social welfare in the U.S. consumer firearms industry. Using microdata from Massachusetts and aggregate data from other states, we estimate an equilibrium model of the consumer firearms industry. To identify price elasticities, we construct an instrument based on heterogeneous exposure to aggregate shocks to the prices of metal commodities. Although firearm manufacturers charge substantial markups, a calibrated model of firearm-related homicide implies that these markups are poorly targeted towards each product's homicide externalities. We consider the redesign of a longstanding federal excise tax on firearms (11% on long guns, 10% on handguns), and show considerable welfare gains from a "second-best" optimal tax scheme under the political-economy constraint that surplus among firearm consumers remains constant. We also construct a simple tax redesign (0% on long guns, 15.5% on handguns) that would capture 80% of the potential welfare gains from the constrained-optimal policy. Either tax redesign would lead to pricing better aligned with social welfare from firearm transactions, while preserving consumer surplus and industry profits and improving public health. Politically conservative regions of the U.S. would benefit disproportionately from these tax reforms, suggesting they may also be politically feasible.

*We are grateful to the Massachusetts Firearms Records Bureau for their assistance in working with the FRB dataset, as well as Matthew Miller for sharing data from the 2015 National Firearms Survey. We also thank Marcella Alsan, Desmond Ang, Jurgen Brauer, David Johnson, Jack McDevitt, Matthew Miller, and Jeffrey Smith for their helpful feedback on this paper, as well as seminar audiences at the NBER Conference on Firearm Markets, Boston University, Georgetown, BSE Summer Forum, and CELS. This project was supported in part via Arnold Ventures Grant#23-10007. This paper was previously circulated as "The U.S. Consumer Firearms Industry: Welfare and Policy Implications".

†Assistant Professor of Public Policy, Kennedy School of Government, Harvard University. email: larmona@hks.harvard.edu

‡Postdoctoral Fellow, Cowles Foundation for Research in Economics Candidate, Yale University. email: adam.rosenberg@stanford.edu

1 Introduction

In 1918, to raise revenue for World War I, the U.S. government levied an excise tax of 10% on sales from firearm manufacturers, with this tax rate left unchanged since 1954 (Congressional Research Service 2023).[1] Beyond taxes, federal regulation of the firearm industry stagnated in the 20 years following the expiration of the Federal Assault Weapons Ban in 2004, in part due to political barriers created by firearm owners and their advocacy organizations (Lacombe 2021). Over this period, the consumer firearms industry has expanded significantly—firearm manufacturers have consolidated into multi-brand conglomerates, innovated an array of products with diverse characteristics, and sold millions of firearms to consumers—bringing the U.S. stock of firearms in 2021 to over 300 million (Brauer 2013, Miller et al. 2022). Beyond its market participants, the allocation from the firearms industry has broad welfare implications, as firearm ownership is also associated with increases in violent crime and harms to public health (RAND 2018). Despite the potential gains from redesigning federal regulations on the firearm industry, including alternate excise taxes, regulators lack evidence on how policy changes would affect market equilibrium and which policies may be both politically-feasible and welfare-improving (Smart 2021).

This paper studies how politically feasible redesigns of federal regulation on firearm manufacturers would affect market outcomes, firearm homicide fatalities, and social welfare in the U.S. To do so, we develop and estimate an equilibrium model of the U.S. consumer firearms industry, from which we simulate the market prices and quantities of firearms under alternate excise taxes. We pair our predictions of firearm quantity flows with a calibrated model of the evolution of state-level firearm stocks and their implications for shooting fatalities, allowing us to quantify a key non-market implication of taxes on the firearm market. Our model reveals allocative inefficiency in the firearm market—due to heterogeneity across firearms in markups and their effects on shooting fatalities—which could be partly addressed through a simple redesign of the excise tax on firearm manufacturers. Tilting the federal rate on handguns to 15.5% and on long guns to 0% would hold nationwide industry profits and consumer surplus constant, prevent 267 fatal shootings between 2016–2022, and transfer surplus to areas with stronger political opposition to firearm regulation.

Politics is often an obstacle to the design and implementation of firearm policy in the U.S., with opposition arising from key consumer segments who may be harmed by a policy change (Gentzkow et al. 2019, Luca et al. 2020). Formalizing this political constraint, Section 2 models a social planner seeking to maximize welfare while facing constraints from the

[1] In 1954, the rates were changed to 10% for pistols/revolvers, and 11% for all other firearms (e.g. rifles and shotguns).

demand-side of the market, requiring that any corrective taxes must leave consumers at least as well off as under the status quo. We interpret this constraint as a stylized representation of the political economy surrounding firearm regulation in the U.S., where well-organized consumer interest groups exert significant influence on policy outcomes (Lacombe 2021). Our analysis of the planner's problem allows us to derive necessary conditions that characterize the constrained-optimal "second-best" taxes on firearms. This tax scheme alters prior results on taxation in markets with negative externalities and imperfect competition (Buchanan 1969, Diamond 1973, O'Connell and Smith 2024) to additionally require lower taxes on products from which consumers derive the most surplus. By the Ramsey (1927) rule, these high-surplus products are (roughly) those for which purchasers are the least price elastic. Thus, the constrained optimal tax scheme preserves the surplus enjoyed by inframarginal consumers, while using high rates to redirect marginal consumers towards products that are less socially harmful.

The key empirical challenge to our analysis of firearm policy is that few datasets match firearm purchase quantities to prices in the U.S. (Moshary et al. 2025), which we overcome by linking a variety of information on the industry, described in Section 3. We access transaction-level microdata with information on the make, model, product characteristics, and buyer geography of every licit handgun and long gun sale by firearm dealers in Massachusetts from 2016-2022, as discussed in Armona and Rosenberg (2024). Since these data do not record transaction prices, we measure prices as MSRPs (Moshary et al. 2025), which we access from an industry publication. To measure firearm demand in the rest of the U.S., we construct a proxy for aggregate quantities of firearm purchases from state-year data on federally-mandated firearm background checks, which we enhance by adjusting for heterogeneity in background check requirements across state-years (Brauer 2013, Smucker et al. 2022).

With these data in hand, Section 4 begins our empirical analysis of firearm regulation by estimating a price elasticity of firearm demand, measuring the extent to which policy changes can shift consumer choices through their impact on prices. We address the potential endogeneity between firearm prices and quantities by constructing a price instrument that isolates cross-manufacturer heterogeneity in exposure to the world commodity prices of metal inputs to firearm production (McDougal et al. 2023). We estimate a price elasticity of firearm demand of -2.5 for consumers in Massachusetts between 2016–2022, suggesting consumers are reasonably responsive to price changes. Because our estimated elasticity represents substitution patterns for the average firearm model, we are unable to distinguish how price changes divert consumers across different firearm models—or towards the decision to not purchase a firearm—which directly appear in our optimal tax formula.

To further understand firearm pricing and its role in the design of firearm regulation, Section 5 develops and estimates an equilibrium model of demand and supply in the firearms industry. We specify demand for heterogeneous firearms as a random coefficients nested logit (Brenkers and Verboven 2006), with consumers' preferences depending on their demographics, a firearm's characteristics, and a number of fixed effects. On the supply-side, we assume that multi-product firearm manufacturers engage in imperfect competition, setting prices to maximize profits while facing competition from pre-existing firearms on the second-hand market and excise taxes on their sales of new firearms.

We identify the demand system by maximizing the likelihood of individual firearm purchases in Massachusetts, while matching moments on market-level product shares, aggregate firearm purchases elsewhere in the U.S., and the orthogonality between demand shocks and supply-side instruments. In line with survey reports, our estimates reveal preferences that vary systematically along geography, race, gender, and voting patterns, as well as limited substitution between handguns and long guns (Azrael et al. 2017, Parker et al. 2017). Beyond substitution between handguns and long guns, our estimated demand system generates the rich patterns of substitution across firearm models that enter our optimal tax formula. Between 2016–2022, the firearm industry delivered \$114 of annual surplus per U.S. adult, or about \$29 billion of annual consumer surplus, indicating consumers derive significant value from access to the firearms market.[2]

On the supply side, we estimate similar average price-cost margins for both handguns and long guns, though there is considerable heterogeneity across firearms within each class. Quantitatively, the average firearm purchased costs \$332 to produce but is priced to consumers at \$716, with producers taking \$310 in profit from the average new gun sale, and the remaining \$74 going to the government as tax revenue. These estimates imply a pre-tax Lerner index of around 0.43 (and post-tax around 0.54), suggesting considerable pricing power among firearm manufacturers, which also enters our optimal tax formula.[3] Annually between 2016–2022, we estimate that the firearm industry generated \$3.3 billion of manufacturer profits and \$0.8 billion of federal tax revenue.

To quantify a key non-market externality of the consumer firearms industry, Section 6 introduces a stylized model linking the quantity demanded of new firearms to the evolution of the firearm stock and firearm homicides. To account for the fact that over 90% of firearm homicides are committed with handguns, despite long guns accounting for nearly half of the U.S. firearm stock (Azrael et al. 2017), our model allows handguns and long guns to

[2]Comparable estimates from Grieco et al. (2023) value the new car market as producing \$600 of consumer surplus for the average U.S. adult in 2016.

[3]For comparison, Grieco et al. (2023) find pre-tax Lerner indices in the U.S. new car market of 0.33 in 1980 and 0.19 in 2018.

heterogeneously affect homicide rates. We calibrate the parameters of this model using estimates from prior studies, with a small number of simple statistics governing the model's behavior.

Due to the significant size of the existing firearms stock, and an estimated average durability of 67 years of each new firearm purchase, we estimate that each new firearm purchase has limited short-run effects on homicides, with each average new firearm purchase causing only 0.000026 homicides in its first year of circulation. These effects accumulate to 0.0018 firearm homicide fatalities over its usable lifetime, or about 1 homicide for every 570 new purchases. At the same time, we estimate that homicides are twice as elastic to state-wide handgun prevalence as to long gun prevalence. Expressing these differences in monetary terms, our estimates imply that each new handgun purchase causes $5,040 of net present harm, while the typical long gun purchase causes only $190 of net present harm.[4] The results strongly suggest that when measured by homicide fatalities, handguns are the socially harmful products in this market[5] and should be the target of corrective taxation.

Section 7 combines our optimal tax results from Section 2 with our fitted models of firearm demand, supply, and homicide to study alternative firearm regulation. We simulate three tax changes: the constrained-optimal tax from our theoretical analysis, a simpler two-tax policy in which the planner holds consumer surplus constant while only "tilting" the relative tax rates on handguns and long guns, and a blunt 11 percentage point increase in the existing federal tax that mirrors existing policy proposals.

All three counterfactual tax increases improve social welfare, with especially large gains over the medium-to-long run.[6] Notably, the tax changes that are politically-constrained by consumer surplus generate larger increases in social welfare despite lowering the average tax rate on firearms. These handgun-only tax systems raise welfare while lowering taxes on firearms due to a targeting gain: they limit taxes on the firearms that are valued by consumers but unlikely to increase homicides, while raising taxes on the firearms that consumers value less or are more likely to cause harm. Moreover, we find that both handgun-only tax systems may be politically feasible, as they cause no systematic harm to consumers across the political spectrum, while providing disproportionate public health benefits to Republican- and NRA-supporting areas. Considering implementation, we view the "tilted" handgun

[4] We use a value of a statistical life of $9.5M and an annual discount rate of 5%. An average durability of 67 years corresponds to an annual degradation rate of 1.5%.

[5] Our calculations do not account for any effects of the firearm stock on incidents of self-harm, nor on broader externalities like social well-being, mental health, or schooling (Pienkny et al. 2024, Cabral et al. 2021).

[6] We measure welfare as the sum of consumer surplus, manufacturer profits, federal tax revenue, and (prevented) firearm homicide fatalities. We value each firearm homicide fatality that does not occur according to a statistical value of a life.

tax as a promising policy option, as it can be implemented with only two tax rates while achieving 80% of the welfare gains from our optimal tax formula.

Our work relates to a growing literature on firearm markets (Koper and Roth 2002, Bice and Hemley 2002, Cook et al. 2007, Knight 2013, McDougal et al. 2023, Hüther 2023, Bollman et al. 2025), and is especially close to two recent papers. Moshary et al. (2025) use a survey experiment and stated preference data to develop and estimate a model of firearm demand in product space, accounting for heterogeneous preferences over eighty firearm models and their hypothetical prices. Rosenberg (2024) uses non-overlapping administrative data from California to estimate a model of consumer preferences for an undifferentiated handgun and the relationship between preferences for handgun purchase and public health costs of handgun ownership. In contrast, we estimate consumer preferences over a firearm's price and its physical characteristics, which we pair with supply-side ownership data to recover the cost structure firearm manufacturers. By pairing our model of the firearm market with calibrated models of the firearm stock and its role in firearm homicides, we provide guidance on the effective design of firearm taxes, a topic that has been under-studied due to limited policy variation (Smart 2021).

We also contribute to a broader literature concerned with the design of regulation to correct externalities in imperfectly competitive product markets (Pigou 1924, Buchanan 1969). Recent work has studied this question in the domains of beverages (O'Connell and Smith 2024, Conlon and Rao 2023) and personal transportation (Barwick et al. 2023). As in these other settings, we find that product-specific allocative distortions due to market power are poorly targeted at the distortions due to consumption externalities. We contribute to this literature by incorporating and implementing political economy constraints into the planner's problem, and showing that the mis-targeting of firearm taxes under the status quo can be corrected in a manner that benefits consumers and producers, while decreasing social harm.

2 Designing Firearm Taxes

We outline a simple optimal tax problem to guide our analysis of tax design in the firearms industry. Unlike other industries where business and trade organizations dominate political influence, interest groups for firearm consumers (e.g. the National Rifle Association and Gun Owners of America) are highly organized and the dominant political force (Boehmke et al. 2013, Laschever and Meyer 2021). With this in mind, we approach the problem of tax design with a view towards political feasibility, by considering a social planner who maximizes social welfare subject to a constraint that consumer surplus does not fall below some pre-specified level. We refer to the resulting tax system as "second-best," since it only maximizes welfare under the political-economy constraint, and not unconditionally.

We define welfare as the sum of consumer surplus CS, producer surplus Π (profits), government tax revenue $\mathcal{G}$, and a negative externality representing the harm caused by the purchase of products, Φ.

$$\mathcal{W} = CS + \Pi + \mathcal{G} - \Phi \tag{1}$$

While in our context, Φ represents public health consequences from increased violence, our framework could be applied to other settings where the consumption of a product generates externalities (e.g., pollution from gasoline consumption).

We consider a setting where the social planner has access to specific excise taxes $\tau_{j,t}$ on each product j in each market t, so that if the firm from prices at $p_{j,t}$, it receives revenue $p_{j,t}$.[7] Inspired by the political power of firearm consumers, we consider a constrained environment where the social planner chooses taxes $\vec{\tau}$ to maximize welfare $\mathcal{W}(\vec{\tau})$, subject to a constraint that consumer surplus does not fall below some pre-specified level CS_0. This problem resembles the classic Ramsey (1927) tax problem, except the regulator must ensure that consumers, instead of the firm, receive a threshold surplus level. The solution to the problem is given below.

Proposition 1. *Suppose that firms engage in Nash-Bertrand price competition, and the social planner chooses specific excise taxes $\tau_{j,t}$ to solve the following optimization problem:*

$$\begin{aligned} \max_{\tau_{j,t}} \quad & \mathcal{W}(\vec{\tau}) \\ s.t. \ \ & CS(\vec{\tau}) \geq CS_0, \end{aligned} \tag{2}$$

where welfare as defined as in Equation 1. Then the constrained-optimal specific tax on product j in market t satisfies:

$$\tau^*_{j,t} = \phi_{j,t} - \mu_{j,t} - \lambda \cdot \mu^M_{j,t} \tag{3}$$

Where $\phi_{j,t}$ is the magnitude of the (negative) marginal externality of product j in market t, $\mu_{j,t}$ is the profit margin charged by the firm, $\mu^M_{j,t}$ is the margin that would be charged under a monopoly ownership of all products, and λ is the shadow price (in welfare units) of the consumer surplus constraint $\partial \mathcal{W}(\vec{\tau}^*)/\partial CS_0$.

Proof. See Appendix OA.1. □

[7] For illustrative purposes, we focus on the specific taxes, though the solution for ad valorem taxes is very similar and given in Appendix OA.1.

To interpret our second-best tax formula, briefly consider the case where $\lambda = 0$, or the consumer surplus constraint does not bind. This corresponds to a first-best solution for the social planner. In this case, Equation 3 requires the planner to equate the gross of tax markup $\tau_{j,t} + \mu_{j,t}$ with the marginal social harm of consumption $\phi_{j,t}$, for each product in each market. This is a standard Pigouvian solution with imperfectly competitive markets (Buchanan 1969).

Our second-best solution has two key differences from this unconstrained benchmark. "Second-best" taxes should be lower overall, to limit harm to consumer surplus, in proportion to the shadow cost of the constraint λ. Moreover, among products with a similar externality, taxes should be lowest on firearms that would have higher margins under monopoly $\mu_{j,t}^M$. This force disproportionately lowers taxes on the products from which consumers derive the highest surplus, since these are the products a monopolist would most mark up. Such cross-product targeting follows an "inverse" Ramsey rule: the optimal tax is *lower* on products with higher margins under monopoly, and hence with *less elastic* demand. Intuitively, price-sensitive consumers reveal they have weaker preferences for a product, so that raising taxes may induce substitution to less harmful products without too much surplus loss among consumers. In essence, our politically-constrained optimal tax formula suggests that policymakers target higher taxes towards socially costly products that provide less benefit to consumers.

Our formula clarifies that, in order to efficiently tax firearms, policymakers need to understand three key objects: (i) the marginal social harm from each firearm purchase, (ii) the price-cost margins charged by firms in equilibrium, and (iii) the counterfactual margins that would be charged under monopoly conduct, as a measure of consumer valuations. Our subsequent empirical analysis is designed to estimate these three objects, which we then use to construct optimal firearm taxes and to simulate the effects of these and other counterfactual policies in Section 7.

3 Setting and Data

This section describes key regulations on the U.S. firearms industry and the data elements used in this paper.

3.1 Firearms and regulation

Firearms are popular consumer products in the U.S., with 40% of U.S. households owning at least one firearm, and consumers purchasing millions of firearms each year (Berrigan et al.

2022). The Second Amendment to the U.S. Constitution protects the right of individuals to "keep and bear Arms." Consumers typically acquire firearms from retailers (e.g., Bass Pro Shops), who themselves are typically served by intermediate dealers (e.g., Davidson's Incorporated) that buy from various manufacturers upstream (e.g., Smith and Wesson). In this paper, we focus on the decisions of consumers and manufacturers, abstracting from other components of the supply chain.

Firearms—having been linked to crime and violence (Duggan 2001, Cook and Ludwig 2006)—are also the subject of many proposed and implemented market regulations. Excise taxes on newly-produced firearms were first set at 10% as part of the Revenue Act of 1918, statutorily paid when a manufacturer sold a firearm. These taxes were raised to 11% through the Revenue acts of 1940 and 1941. The Excise Tax Reduction Act of 1954 set the tax on handguns to 10% and on long guns to 11%, and these rates have not been adjusted since. Many states require that consumers pay a one-time fee prior to their first in-state firearm purchase (e.g., New Jersey). Beyond taxes, there are restrictions on the types of firearms that may transact in the U.S. The 1934 National Firearms Act placed federal restrictions on the ability of consumers to own fully-automatic firearms (i.e., machine guns), later extended to other destructive devices (e.g., grenades). From 1994–2004, the Federal Assault Weapons Ban prevented the purchase of newly produced "assault weapons" (e.g., semi-automatic long guns like the AR-15). Although no longer federal law, several states including Massachusetts, maintain such assault weapon bans.

Federal law in 1994—the Brady Act—also began mandatory background checks prior to certain firearm purchases. These background checks are implemented by the FBI under the National Instant Criminal Background Check System ("NICS"). States are given some leeway in the design of their background check system, with several states including Massachusetts, mandating background checks before every firearm transfer.

Firearm markets across states maintain distinctive character. The Gun Control Act of 1968 banned transaction of firearms across state lines except by individuals with a Federal Firearms License ("FFL"). Federal law sets minimum standards for registration as an FFL, with states able to set more stringent regulations. In addition to the state regulations above, states and localities also differ in their policies on where firearms may be carried, how firearms may be used, and how transfers are recorded.

3.2 Market size and consumer demographics

We define a market for legal consumer firearms by state-year. Within a state, we measure the size and demographic characteristics of each zip code's adult population using the 5-

year estimates from the (2015-2019) American Community Survey. We also measure each zip codes' conservative vote share in the 2016 Presidential Election (Martin and Yurukoglu 2017).[8] As a measure of firearm-specific political engagement, we measure each donations from each zip code to the National Rifle Association as reported to the Federal Election Commission, as well as a record of the NRA's grading of its representative to the U.S. Congress in 2018.[9]

Some adults within each zip code may have no interest in owning a firearm, a fact incorporated into our definition of market size (Stantcheva 2025). We measure those potentially interested in firearm ownership using a survey of 3,900 U.S. adults from 2017, linking respondents' stated personal firearm ownership and interest in becoming a firearm owner with their demographic and political characteristics (Parker et al. 2017). Our procedure mirrors the approach of Backus et al. (2021) and predicts market size by regressing a binary indicator for each respondent's (interest in) firearm ownership on their characteristics, with adjustments for geographic heterogeneity and high-dimensional regressors described in Section OA.2.1. We use the coefficients from this regression to linearly transform each zip code's overall adult population into the subset of its adult population interested in firearm ownership.

Our procedure measures the market size for legal firearms as about two-thirds of the adult population. Figure OA.1 shows that men, U.S. citizens, and Republicans are over represented in the firearm market.

3.3 Microdata on firearm purchases within Massachusetts

Within Massachusetts, we use administrative microdata on the universe of firearm transactions involving FFLs as recorded by the state's Firearm Record Bureau's (FRB), representing the universe of new firearm purchases.[10] Each time a consumer purchases a firearm in Massachusetts, state law requires the seller to perform an electronic verification of the consumer's firearm purchase license. Our data is the publicly available list of all such verifications by FFLs in Massachusetts.[11] With our focus on behavior in the new firearm market, we do not use the FRB's information on the less-frequent sales of firearms by private individuals, as

[8] We do so by projecting precinct-level vote shares from Voting and Election Science Team (2018) onto zip codes based on geographic overlap of the regions, weighted by total number of votes.

[9] NRA donation data is downloaded from `https://www.fec.gov/`. NRA grade data was collected from `https://www.everytown.org/nra-grades-archive/`

[10] Other papers using these data include Braga and Hureau (2015), Iwama and McDevitt (2021), Balakrishna and Wilbur (2022), and Johnson et al. (2023).

[11] Available at `https://www.mass.gov/info-details/data-about-firearms-licensing-and-transactions`

sales by private individuals are definitionally sales of used firearms.[12]

Each transaction in these data is tagged with additional information. The FFL manually inputs information about the firearm itself, including its manufacturer (e.g., Colt), model (e.g., Python), firearm class (handgun or long gun), and physical characteristics (caliber, barrel length, and a flag for high capacity). The FRB provides information about the consumer—including their gender and residential zip code—by merging to their state-issued firearm license. The FRB verification system itself records the transaction date.

We process the underlying FRB data for use in our analysis. We convert calibers to a standard unit of inches across all firearms, as caliber can be recorded as inches, millimeters, or gauge (for shotguns). We perform a similar standardization for barrel length. We manually standardize the manufacturer field for any manufacturer with at least 30 purchases in these data.

Our analysis uses an informative subset of these transaction records. Although the FRB began recording these data in 2006, they began tracking whether firearms are high capacity in 2016, and we focus on the period 2016–2022 to include this variable in our analysis.

Table 1 shows how demographics of the Massachusetts adult population map onto the characteristics of consumers in the market for firearms. Relative to the average adult, gun purchasers are more likely to be male, and live in less racially diverse, more rural, and more politically conservative neighborhoods. These differences are more pronounced among long gun purchasers (relative to handgun purchasers).

Figure OA.7 shows that the purchase of handguns has been roughly constant at 65% from 2016–2022, while the purchase of used firearms increased from 20% to 40% over this same period. The timing of the shift towards used guns in the market is consistent with anecdotal evidence that during the COVID-19 Pandemic, many firearm manufacturers reached binding capacity constraints and were unable to keep up with the surge in firearm demand.[13]

A limitation of the FRB data is that they do not record the prices at which firearms transact. Nor is the literature aware of any dataset recording both firearm prices and transaction quantities (Moshary et al. 2025).

3.4 The Blue Book of Gun Values and firearm prices

For information on firearm prices, we use historical data from the Blue Book of Gun Values (BBGV), an industry pricing guide. For each manufacturer-model, BBGV records the

[12] Massachusetts state law allows a private individuals to sell four or fewer firearms each calendar year (MA G. L. c. 40 §128A)

[13] See for example https://cbsaustin.com/unprecedented-demand-on-guns-and-ammo-putting-pressure-on-supply-chain

years in which it was actively produced and each year's manufacturer suggested retail price (MSRP). As prices quoted by firearm retailers across the U.S. cluster around the MSRP (Moshary et al. 2025), we assume that new firearms are priced nationally and that that price facing consumers is the MSRP.

By subscribing to BBGV, we used an automated procedure to check whether each manufacturer-model-year present in the FRB data from 2016–2022 was under active production, and if so, to record its price. The key challenge in our procedure is that the firearm manufacturers and models in the FRB dataset are entered manually, and so are not standardized across records. As such, our procedure uses fuzzy string matching, described in detail in Section OA.2.3, to link these two datasets. We are able to match 90% of purchases in the FRB to a unique manufacturer-model in BBGV, with about 70% of these matched purchases occurring while the firearm was under active production (i.e., having an MSRP). Throughout our analysis, we assume that if a firearm was purchased from an FFL during a year in which it was under active production, then it was the purchase of a new (not used) firearm.

Table 2 displays summary statistics on firearms in our dataset. Handguns typically have a shorter barrel length and lower in caliber than long guns (rifles and shotguns), though Figure OA.6 shows there is considerable heterogeneity in barrel length and caliber across firearms, even within a firearm class. We also show transaction-weighted averages, which reveal that Massachusetts consumers tend to purchase guns that are cheaper (relative to those available), and more likely to be high-capacity and an actively produced weapon. The average new firearm purchased is around \$900, with handguns are typically being cheaper than long guns.

Figure OA.8 shows that there is considerable price dispersion, even within firearm class. For instance, in 2016, the typical handgun sold just under \$800 (interquartile range \$600-\$900), while the typical long gun sold for \$1,100 (interquartile range \$500-\$1,300). Figure OA.9 shows that, within a firearm model, prices remained roughly constant from 2016–2020, before increasing by 8% from 2020-2022. Thus sudden price increase is possibly attributable to the supply chain issues that plagued many industries in the U.S. during the COVID-19 Pandemic, and may have particularly affected the costs of raw manufacturing inputs to firearms (e.g., steel). [14]

[14] See, for example: https://shootingindustry.com/discover/supply-chain-woes/

3.5 Auxiliary Datasets

Aggregate firearm purchase quantities We measure aggregate quantities of firearm purchases in each state-year by developing and applying an adjustment to publicly available data on NICS background checks. Background checks are are a common proxy for firearms purchases (Lang 2016), but suffer from reporting biases due to state-year differences in background check requirements (Smucker et al. 2022). For example, in some states, firearm permit holders are exempt from background checks when purchasing an additional firearm, which would otherwise bias our estimates of total purchases downwards. We account for these differences in our adjustment procedure, which is described in detail in Section OA.2.2, with specifics in Tables OA.1–OA.4 and Figures OA.2–OA.3.

Firearms stock Because firearms are durable goods, we require a measure of total guns in circulation to predict public health effects of transactions. To measure the overall firearm stock, we use published estimates of the count of firearms in the U.S. in 1996 and 2015 (Cook and Ludwig 1996, Azrael et al. 2017). We also use administrative estimates of the inflow of firearms into the U.S.—newly manufactured domestic firearms less net exports—from the Bureau of Alcohol, Tobacco, and Firearms (ATF).[15]

We also bring together information on the distribution of the firearm stock across U.S. households. For this information, we gather data on the count of households per state from the 2015 ACS, the share of U.S. adults living with a firearm in their household in 2015 by state from Schell et al. (2020), the average number of firearm owners living with each firearm outing adult in 2015 from Azrael et al. (2017), and the average number of firearms owned by each firearm owner in 2015 by census region and firearm class from Azrael et al. (2017).

Firearm homicides Our analysis of firearm homicides uses standard sources of publicly available state-year data from 2016–2022: counts of firearm homicides from the Current Final Multiple Cause of Death Data from the National Center for Health Statistics, and the share of firearm homicides by firearm class (or unknown) from the National Violent Death Reporting System.[16]

Ownership of firearm manufacturers We manually reconstruct a panel of entities owning each of top 99 firearm manufacturers by sales volume in Massachusetts. Our reconstruction uses information on the historical merger and acquisition activity of these manufactures, drawing primarily on histories from BBGV and the manufacturers' own websites.

[15] ATF data is downloaded from https://www.atf.gov/resource-center/data-statistics.

[16] Data for both are downloaded from https://wisqars.cdc.gov/.

This procedure captures the fact that, although the FRB and BBGV datasets record firearm manufacturers, multiple manufacturers may be wholly owned by a single parent company.[17]

Figure OA.10 shows the share of ATF firearm production in the U.S. accounted for by the top-four parent companies each year. The four largest manufacturers account for at least half of total firearm production each year, and around two-thirds of production within each firearm class.

4 Pricing in Firearm Markets

In this section, we introduce a cost shock to firearm manufacturing. We use this shock to study the price elasticity of consumer demand for firearm models.

4.1 Constructing cost shocks

Our analysis uses shocks to the input costs of firearm production as instruments for price, a popular approach in the demand estimation literature (Berry and Haile 2021). This instrument is likely to work well in the firearms industry, where much of the costs of manufacturing are tied up in the purchase of materials—such as steel and aluminum—that transact on the world commodity market, and consistent with prior approaches to estimating firearms price elasticities (McDougal et al. 2023).[18]

As we do not observe the exact mix of inputs used to produce a firearm, our strategy isolates cost shocks in the spirit of Villas-Boas (2007), by flexibly approximating the production and pricing practices of different manufacturers. Specifically, we assume that the following price regression holds:

$$\log(p_{j,t}) = \underbrace{\tilde{\gamma}_j}_{\text{Gun FE}} + \underbrace{\tilde{\eta}_{c(j),t}}_{\text{Class-Year FE}} + \sum_{k \in \mathcal{K}} \underbrace{\left(\beta_{m(j),k} \log(\tilde{p}_{k,t})\right)}_{\text{Pass through}} + \epsilon_{j,t}, \tag{4}$$

in panel data on firearm j, of firearm class $c(j)$, produced by manufacturer $m(j)$ during year t. The summation is over different inputs to firearm manufacturing k, each with world commodity price $\tilde{p}_{k,t}$. We measure commodity prices $\tilde{p}_{k,t}$ by aggregating the monthly Producer

[17] For example, the Italian firearm manufacturer Beretta wholly owns the other Italian firearm manufacturers of Benelli and Franchi.

[18] Intermediate inputs account for 65% of the costs of firearm manufacturing, with 35% of intermediate expenditures on primary metals (e.g. steel) and fabricated metal products (e.g. iron molds). Statistic calculated using "Ammunition, arms, ordnance, and accessories manufacturing" category via 2017 input-output tables from https://www.bea.gov/data/industries/input-output-accounts-data, excluding inputs from the same commodity category.

Price Index to annual frequency, with a base year of 2016.[19] Our preferred specification of inputs $\mathcal{K}$ is the set of 6-digit commodities in the PPI that begin with 101 and 102—denoting iron/steel and nonferrous metals, respectively—giving us $|\mathcal{K}| = 51$ commodity price time series from carbon steel scrap to copper ore. Figure OA.11 shows considerable annual variation in the world prices of metal commodities k that we use for estimation. The largest shock to these input prices coincides with the COVID-19 pandemic over 2021–2022, which both spurred a series of global supply chain issues and drove U.S. demand for firearm purchase to historic highs (Sokol et al. 2021).

The parameter $\beta_{m,k}$ in Equation 4 governs the average pass through of the world commodity price $\tilde{p}_{k,t}$ into firearm prices $p_{j,t}$ for each manufacturer-commodity pair m, k. Since we include fixed effects for firearm $\tilde{\gamma}_j$ and firearm class-year $\tilde{\eta}_{c(j),t}$, the parameter $\beta_{m,k}$ specifically measures the *heterogeneous responsiveness* of manufacturers' prices to common input cost shocks, residualizing price variation attributable to aggregate shocks such as COVID. [20]

For our analysis sample, we limit our attention to all firearm models with at least 100 purchases in Massachusetts from 2016–2022, giving us 422 unique firearm models produced during our sample by 66 manufacturers. These account for 93% of new firearms purchases in Massachusettsduring this period. With 51 potential commodity inputs, this implies $\dim(\vec{\beta}) = 66 \times 51 = 3,366$ potential parameters to estimate, meaning our 2,464 model-year observations cannot fully identify the parameter $\vec{\beta}$. Even if we pruned commodities $\mathcal{K}$ further to achieve identification, small sample variability and a weak instruments problem may pollute our estimates of pass through $\beta_{m,k}$ and limit their informativeness.

To address this, we estimate the pass-through parameters $\beta_{m,k}$ using the dimension-reduction procedure of Belloni et al. (2012). This approach first estimates Equation (4) via lasso—using a data-driven penalty based on econometric theory and the assumption of independent but heteroskedastic errors $\epsilon_{j,t}$—to select a subset of parameters $\beta_{m,k}$ for inclusion in the model. Following model selection of $\beta_{m,k}$, we estimate Equation (4) via OLS, zeroing out the un-selected pass-through parameters. Heuristically, this procedure finds and estimates the subset of manufacturer-commodity pass through parameters $\beta_{m,k}$ that can be most feasibly differentiated from one another in the available data. Though this procedure utilizes the role of metals in firearms production, the underlying empirical

[19] See https://download.bls.gov/pub/time.series/wp/wp.txt for a description of the dataset.

[20] For example, if a manufacturer primarily uses carbon steel scrap to produce firearms, they will be more exposed to the jump in the carbon steel scrap price in 2021, relative to a manufacturer that uses other metals during production, and so would have a positive coefficient $\beta_{m,\text{carbon steel scrap}}$. The primary threat to identification would be if demand shocks, such as COVID-19, were correlated with the reliance of certain manufacturers on particular inputs. This could occur if the surge in gun demand during COVID-19 was driven by a surge in demand for guns made out of carbon steel scrap specifically.

approach is more general. Our combination of heterogeneous supplier exposures developed in Villas-Boas (2007) with the dimensionality reduction techniques of Belloni et al. (2012) is agnostic to the specific inputs governing production and could be applied to other settings.

Figure OA.12 displays our estimates of the selected pass-through parameters $\hat{\beta}_{m,k}$. From the potential set of 3,366 such parameters, 6 are selected, suggesting that many of the manufacturer-specific coefficients are uninformative about firearm pricing. The 6 selected pass-through parameters are associated with some of the largest firearm manufacturers, covering 40% of the firearm models in our sample. This ensures that the cost shocks we study impact a wide range of firearms across the industry.

Figure 1 displays the role of our estimated cost shocks—$\sum_k \hat{\beta}_{m,k} \log(\tilde{p}_{k,t})$—in driving observed firearm prices. In aggregate, these cost shocks faithfully reconstruct the times series of prices within a firearm over time. Moreover, these shocks drive considerable variation in firearm prices, spanning price change from -5%–5%.

4.2 Price elasticity of firearm demand

We use our estimated cost shocks—$\sum_k \hat{\beta}_{m,k} \log(\tilde{p}_{k,t})$—to measure a price elasticity of firearm demand among consumers in Massachusetts.

Specifically, we estimate the equation

$$IHS(q_{j,t}) = \gamma_j + \eta_{c(j),t} + \alpha \log(p_{j,t}) + \xi_{j,t}, \tag{5}$$

using the same firearm-year panel data as our estimates of Equation (4). The dependent variable is the inverse-hyperbolic sign of purchases of firearm j by consumers in Massachusetts during year t.[21] Analogous to Equation (4), we model this measure of firearm purchase quantity $IHS(q_{j,t})$ as a function of fixed effects for firearm model γ_j and weapon-class year $\eta_{c(j),t}$, the log of the firearm's price $\log(p_{j,t})$, and an unobserved demand shock $\xi_{j,t}$.

The parameter of interest is α, which governs the price elasticity of firearm demand. This elasticity captures changes in consumer behavior at the level of the firearm model j, capturing adjustments in demand along both the extensive margin (buying no gun) and intensive margin (buying a different gun).

A challenge to estimating the elasticity of demand α is the endogeneity of price and quantity. In Equation (5), this behavior would manifest as a positive correlation between prices $p_{j,t}$ and demand shocks $\xi_{j,t}$, even conditional on the fixed effects. To address this, we

[21] $IHS(x) = \log(x + \sqrt{1 + x^2})$. We use this transformation, rather than the natural logarithm, to avoid composition bias from dropping the one-third of firearm-year observations with zero sales. Results are very similar if we use the $\log(1 + x)$ transformation.

estimate the elasticity of demand $\hat{\alpha}$ using the instruments described above as a first stage. We do so via the LASSO-IV procedure of Belloni et al. (2012), which produces asymptotically valid standard errors for the second stage.

Table 3 shows our preferred estimate of the price elasticity of firearm demand is $\hat{\alpha} = -2.5$. The reported sup-score test-statistic confirms that our excluded instruments are relevant in predicting prices.[22] This estimate implies that consumers are somewhat responsive to the price when choosing among different firearm models. Our estimate of the firearm-specific price elasticity is larger than the survey-based estimates of Moshary et al. (2025), though both estimates imply that consumers are price conscious when choosing among firearm models.

Table OA.5 shows that our estimated elasticity is not sensitive to the granularity with which we specify the commodities in our cost shock instrument. A consequential decision, however, is the use of instrumental variable to estimate the elasticity, as its OLS analog would incorrectly suggest that consumers are price inelastic in their choice of firearm.

Our estimate of the price elasticity of firearm demand is specific to the average firearm model spanned by our instruments, limiting its interpretation. This elasticity speaks neither to which, if any, different firearm a consumer might purchase because of a price change; how these patterns of substitution differ across firearms; nor to price elasticities among consumers of firearms not spanned by our cost-shock instrument. The following section addresses these limitations by imposing additional structure from a model of supply and demand in the U.S. firearm industry.

5 An Equilibrium Model of the Legal Firearms Market

This section specifies and estimates a model of supply and demand in the U.S. firearms market. The model allows a richer measure of the price elasticity of firearm demand, capturing the manner in which own- and cross-price elasticities vary across different firearms and the no-purchase outside option. The model also allows us to measure the costs to manufacturers of firearm production, enabling a richer understanding of their pricing behavior. In Section 7, we use estimates from our model as a key input to our analysis of counterfactual taxes on the firearm market.

[22]The test statistic's value of 12.55 is well above the critical value of 4.56 needed for 1% significance.

5.1 Demand

We model market demand for firearm j of firearm class $c(j)$ with price $p_{j,t}$ and observable characteristics X_j.[23] There are $\mathcal{J}_t$ firearm models under active production ("new") available each year t, constant across consumers.[24] Consumers may also choose to purchase a used firearm no longer in production or to purchase no firearm at all.

Demand during year t in state s arises from the discrete choice decisions of consumers i with observable demographics D_i.[25] There are M_s consumers in state s, with both mass and demographic distribution constant across years t.

Indirect utility to consumer i from purchasing new firearm $j \in \mathcal{J}_t$ is

$$\begin{aligned} u_{i,j,s,t} &= \overbrace{-\alpha_i p_{j,t}}^{\text{price}} + \overbrace{\beta_i X_j}^{\text{characteristics}} + \overbrace{\delta_{j,s,t}}^{\text{fixed effects}} + \overbrace{\epsilon_{i,j,s,t}}^{iid \text{ shock}} \\ u_{i,0,s,t} &= \epsilon_{i,0,s,t}, \end{aligned} \tag{6}$$

with $u_{i,0,s,t}$ the indirect utility of choosing to not purchase a firearm.

The first term is consumer i's disutility from the price of a firearm $p_{j,t}$. We assume that the price coefficient α_i is *iid*, following the log-normal distribution

$$\log(\alpha_i) \sim N(\alpha + D_i \Pi_\alpha, \sigma_\alpha).$$

The mean is governed by scalar α and vector of demographic shifters Π_α, and the variance is σ_α. The log-normal specification ensures that all consumers dislike price, or $\alpha_i < 0$.

The second term governs consumer i's preferences over the observable characteristics of firearms X_j. We assume that these preferences β_i are *iid*, following the multivariate normal distribution

$$\beta_i \sim MVN(\beta + D_i \Pi_\beta, \Sigma_\beta).$$

The mean is governed by the vector β and the matrix of characteristic-by-demographic shifters Π_β. Throughout, we assume that conditional on observable demographics D_i, the price coefficient α_i and each element of the preferences for observable characteristics β_i are

[23]Observable characteristics X_j are a vector of caliber, barrel length, an indicator for high-capacity, indicators for long guns and shotguns, and a constant.

[24]The choice set $\mathcal{J}_t$ contains all firearm models under active production during year t that have at least 50 observed transactions in Massachusetts and a price below \$2,500. These represent about 60% of all transactions, and about 85% of new firearms transactions. We group all other firearms into a composite outside good, as described below.

[25]Observable demographics D_i are a vector of an indicator for female and—measured for i's zip code—the percent white, percent conservative, log median household income, and log population per square mile.

mutually independent, of which a consequence is that the variance-covariance matrix Σ_β is diagonal.

We specify the fixed effects in indirect utility $\delta_{j,s,t}$ across several hierarchies

$$\delta_{j,s,t} = \delta_j + \tau_{s,t} + \phi_{c(j),t} + \xi_{j,t}. \tag{7}$$

The first term δ_j adjusts for time invariant characteristics of firearm j that may not be observed in data (e.g., the quality of its firing mechanism). The aggregate shocks $\tau_{s,t} + \phi_{c(j),t}$ adjust for changes in preferences for firearm purchase across state-years (e.g., police funding) and by firearm class-year (e.g., a spike in handgun demand during the COVID-19 pandemic), respectively. The final term $\xi_{j,t}$ reflects other time-varying determinants of aggregate demand for firearm j (e.g., a national advertising campaign). Notably, the only component of the fixed effect that varies across states is $\tau_{s,t}$, which is also constant across firearms.

The remaining term $\epsilon_{i,j,s,t}$ is an *iid* shock across consumers, which we assume follows a three-level nested logit (Train 2009). Within a consumer-state-year *ist*, our specification of $\epsilon_{i,j,s,t}$ allows for a heterogeneous distribution between handguns and long guns, as well as a heterogeneous distribution between the purchase of any firearm and the no-purchase outside option. Specifically, we assume:

$$\epsilon_{i,j,s,t} = \zeta_{i,0,s,t} + \rho_0 \zeta_{i,c(j),s,t} + \rho_1 \tilde{\epsilon}_{i,j,s,t},$$

for $\zeta_{i,0,s,t}$ a preference shock to the outside option, $\zeta_{i,c(j),s,t}$ a preference shock to the purchase of firearms in weapon-class c, and $\tilde{\epsilon}_{i,j,s,t}$ a firearm-specific preference shock.[26] The parameter $\rho_0 \in (0, 1]$ controls the correlation of preferences across firearm classes, relative to the outside option, while parameter $\rho_1 \in (0, \rho_0]$ controls the correlation of preferences across firearms within a firearm class. The shocks follow a standard multinomial logit when $\rho_0 = \rho_1 = 1$

As firearms are durable goods, consumers may also choose to purchase a firearm not under active production ("used"), which we model as a firearm class-specific aggregate product ω_c. Each consumer's choice set in period t is thus $\mathcal{J}_t \cup \{\omega_c\}_c \cup \{0\}$. Indirect utility from a used firearm of class c is

$$u_{i,\omega_c,s,t} = \beta_{i,\omega} + \delta_{\omega_c,s,t} + \epsilon_{i,\omega_c,s,t}$$
$$\beta_{i,\omega} \sim N(D_i \Pi_\omega, \sigma_\omega),$$

analogous to new firearms in $\mathcal{J}_t$. Consumer i's preference for used firearms is *iid* Normally

[26]The shocks $\zeta_{i,0,s,t}$ and $\zeta_{i,c(j),s,t}$ follow the unique distribution conjugate to the type 1 extreme value, such that $\tilde{\epsilon}_{i,j,s,t}$ is itself type 1 extreme value (Cardell 1997).

distributed with mean governed by the parameter vector Π_ω; variance equal to σ_ω; and mutually independent from preferences for new firearms (α_i, β_i), conditional on their demographics D_i. We extend the fixed effects $\delta_{\omega_c,s,t}$ and nested logit structure $\epsilon_{i,\omega_c,s,t}$ for used firearms using the same hierarchy as for new firearms.[27] For parsimony, the used-good composite ω_c contains all firearms from 2016–2022 that are not under active production at any point (82% of used-good transactions), have fewer than 50 total purchases in Massachusetts (16%), or are ever priced at \$2,500 or higher (1%), thus representing all other firearms purchased.

5.2 Supply

We model the pricing decisions of firms f that wholly own a set of firearm manufacturers. Firms compete in static Nash-Bertrand fashion each year, simultaneously setting nationwide prices on the firearm models under active production by all their wholly-owned manufacturers $\mathcal{J}_{f,t}$. For each unit of firearm j sold, its owning firm must pay its year-specific, constant marginal cost of production $c_{j,t}$ and the federal excise tax with *ad valorem* rate v_j.

We assume that each firm sets prices to maximize its profits each year, treating as exogenous its set of firearms $\mathcal{J}_{f,t}$, the firearms of its competitors $\mathcal{J}_{f',t}$ and, the evolution of these sets over time. We also assume that used firearms in ω_c are competitively supplied, such that firm pricing of new guns cannot affect the price of used firearms.

These assumptions imply the following problem of setting prices to maximize profits

$$\max_{\vec{p}_{f,t}} \sum_{j' \in \mathcal{J}_{f,t}} q_{j,t} \times (p_{j,t}(1 - v_j) - c_{j,t}), \tag{8}$$

where $\mathcal{J}_{f,t}$ is the set of firearms produced by firm f during year t, $\vec{p}_{f,t}$ is its vector of prices, and $q_{j,t}$ is the yearly quantity of firearm j sold nationwide. This problem has $|\mathcal{J}|_{f,t}$ first order conditions for profit maximization each firm-year, which if unique, exactly govern pricing behavior.

5.3 Estimation & Identification

This section provides an overview of the steps to estimate the parameters in our model and the data that identifies each parameter. Additional details and computational specifics are provided in Appendix OA.3.

First, we jointly estimate the mean utilities of firearms each year $\delta_{j,t} = \delta_j + \phi_{c(j),t} + \xi_{j,t}$ and the parameters governing preference heterogeneity $\Theta = (\rho_0, \rho_1, \alpha, \Pi_\alpha, \sigma_\alpha, \Pi_\beta, \Sigma_\beta, \Pi_\omega, \sigma_\omega)$, us-

[27] Specifically, fixed effects are $\delta_{\omega_c,s,t} = \delta_{\omega_c} + \tau_{s,t} + \phi_{c(\omega_c),t} + \xi_{\omega_c,t}$. For the nesting structure, we place used firearms ω_c in their respective bottom-level nests, alongside the new firearms of the same class.

ing data on firearm purchases in Massachusetts and a constrained MLE procedure (Goolsbee and Petrin 2004, Train 2009). Through this procedure, the heterogeneous tastes for characteristics $(\Pi_\beta, \Sigma_\beta)$ and prices $(\Pi_\alpha, \sigma_\alpha)$ are identified by variation in purchasing patterns within and between demographic cells of consumers in Massachusetts.

To identify the mean utilities $\delta_{j,t}$, the mean taste for prices α, and the nesting parameters (ρ_0, ρ_1), we include the following constraints on the standard MLE objective:

$$0 = Pr_{s,t}(j) - \hat{s}_{j,s,t} \quad \forall j \in \mathcal{J}_t, \text{ all } t, \ s = \text{MA} \tag{9}$$

$$0 = E[\xi_{j,t} \cdot \vec{Z}_{j,t}] \tag{10}$$

$$0 = E[\phi_{c,t} \cdot \tilde{J}_{c,t}] \quad \forall c \in \{h, l\}. \tag{11}$$

Equation (9) ensures that the market-level probabilities of choosing each firearm implied by the model $Pr_{s,t}(j)$ are equal to those observed in the microdata from Massachusetts $\hat{s}_{j,s,t}$, identifying the mean utilities $\delta_{j,t}$ associated with each product. We then regress these mean utilities $\delta_{j,t}$ on the set of fixed effects outlined in Equation (7) to recover estimates of δ_j, $\phi_{c,t}$, and $\xi_{j,t}$.[28] We further project estimates of the product fixed effects δ_j onto firearm characteristics X_j, using the approach of Nevo (2000) to recover baseline tastes β.

Equation (10) ensures that the unobserved product-year demand shocks are uncorrelated with a two-vector of cost-shock instruments $\vec{Z}_{j,t}$. The first instrument is the cost shock from commodity metals described in Section 4.1. This instrument isolates exogenous variation in firearm prices, which serves to identify the (log of the) mean price coefficient α.

The second cost-shock instrument in $\vec{Z}_{j,t}$ is a variant of the differentiation instruments proposed in Gandhi and Houde (2019). This instrument measures the magnitude of cost shocks facing a firearm j, relative to cost shocks of rival products j' in the same class. Such variation affects the pricing behavior and market shares across firearms within the same class, which serves to identify the lower-level nesting parameter ρ_1 (Verboven 1996).

Our final pair of constraints in Equation (11) uses variation in the size of the choice set to identify the outside option nesting parameter ρ_0 (Miller and Weinberg 2017, Gandhi and Nevo 2021). We enforce that the class-year preference shocks $\phi_{c,t}$ are uncorrelated with variation in the (de-meaned) count of firearm models $\tilde{J}_{c,t}$ in each class-year. Figure OA.13 visualizes the year-to-year variation in the size of consumer choice sets.

Our only remaining demand parameters are the state-year vertical taste shocks $\tau_{s,t}$, which we estimate using measures of firearm purchasing across other state-years. Specifically, and

[28] The state-year taste shifters are normalized to zero in Massachusetts each year.

analogously Equation (9), we estimate $\tau_{s,t}$ by satisfying a set of constraints

$$0 = Pr_{s,t}(j \neq 0|\tau_{s,t}) - \hat{s}_{1,s,t} \quad \forall s, t \tag{12}$$

requiring that the inside share predicted by our model aligns with the inside share observed in NICS data $\hat{s}_{1,s,t}$ each state-year. Thus, our estimate of $\tau_{s,t}$ captures the residual differences in firearm purchasing not explainable by differences in demographics or market structure across states-years.

With a fully-estimated demand system, we then recover the unobserved marginal costs $c_{j,t}$ of newly produced firearms using the first order conditions implied by profit maximization in Equation (8).

5.4 Results

Table OA.6 presents the full estimates of model parameters governing preference heterogeneity. Our estimates suggest that neighborhood characteristics capture significant differences in preferences for firearms. For example, those in more conservative neighborhoods have a stronger taste for any firearm, but particularly rifles and higher caliber weapons. Figure OA.14 presents the distribution of state-year taste shocks $\tau_{s,t}$ across the United States. The figure shows considerable variation in the taste for firearms driven by unobservable factors, ranging up to a \$300 (relative to Massachusetts).

Panel (a) of Figure 2 combines both state and demographic variation in preferences to show the consumer surplus created by the firearm industry at the observed equilibrium across U.S. states. The average consumer derives \$152 of surplus each year from the status quo operation of the firearm industry. Across the U.S., this produces \$29.15 billion of surplus each year, or approximately \$114 per adult. This surplus varies considerably across states, with consumers in the South and Mountain-West tending to derive more surplus than consumers along the coasts and near the Great Lakes.

Panel (b) shows that consumers who derive more surplus from the firearms industry are also disproportionately likely to live in congressional districts with many large donations to the NRA. Figure OA.16 shows that these consumers are also more likely to live in areas where their U.S. House Representative is highly rated by the NRA, even among Republican House Representatives. These patterns suggest that consumer surplus and the political economy of gun regulation are closely related, motivating our consumer surplus constraint on the optimal taxes derived in Section 2.

Figure OA.17 unpacks patterns of substitution across U.S. consumers. We find an average own-price elasticity of firearm demand of around -2.6—similar to the aggregate two-stage least-squares estimate from Section 4—though elasticities range from around -1 to -4. Our estimated diversion ratios imply that handguns and long guns are poor substitutes for one another, that consumers easily substitute between new and used firearms, and that a meaningful share of firearm purchasers are just-indifferent to the no-purchase outside option.

Turning to supply, Figure OA.18 presents estimates of marginal costs to firearm manufactures. We find that the typical firearm has a post-tax Lerner Index of between 0.3–0.4. Our model also implies that about \$3.3 billion is generated each year in firearm industry profits, which is comparable to industry estimates of \$2 billion during our sample period (Khaustovich 2025). Our estimates also imply that long guns are more expensive to produce than handguns, as are firearms with higher capacity, higher caliber, and longer barrel length.

Figure OA.15 shows a close alignment between the predictions of our model and several out-of-sample moments of the national firearms industry, computable from other data sources. Our model captures the time-series of tax revenue generated by the firearms industry, the distribution of firearm productions across manufacturers, and cross-state variation in firearm class purchase rates. Our model also produces state-year shocks that are orthogonal to state-level conservative vote shares, suggesting our demographic preferences estimated in Massachussetts project well to other states. Further details describing these out-of-sample moments can be found in Appendix OA.3.2.

Summarizing the welfare-relevant lessons of our model, Figure 3 decomposes the surplus from the purchase of a typical handgun across industry participants. Firms price the typical handgun at \$830. Consumers of the typical handgun are willing to pay \$1,060, such that consumers receive $(1,060 - 830)/1,060 \approx 22\%$ of the potential surplus (i.e, area below the demand curve) from the typical handgun purchase. Firms pay \$420 of cost to sell the typical handgun, implying that such a sale generates \$330 of profit and \$80 of tax revenue, or 39% of potential surplus as costs, 31% as profit, and 8% as tax revenue for the federal government. Prices and costs are somewhat higher for long guns, though they generate similar divisions of potential surplus among industry participants. Figure OA.19 shows a similar decomposition of surplus when weighting firearm-years by their model-predicted purchase frequencies.

These divisions of surplus consider only the short-term implications of firearm purchase among industry participants. The follow section extends our model to account for the implications of firearm purchase on aggregate homicides over the long term.

6 A Model of the Firearm Stock and Homicides

This section specifies a stylized model connecting the flow of firearms in a market to public health consequences, via firearm homicides downstream. Although stylized, our model accounts for three key forces connecting firearms to homicides: (i) firearm homicides are a function of the stock of firearms in a market, (ii) firearms are durable goods that persist in a geographic market over time, and (iii) firearms affect downstream homicide outcomes differentially, depending on their characteristics. Rather than attempting to estimate the causal effects of firearm purchases on homicides directly, we instead calibrate our model using existing estimates from the literature.

6.1 Model structure

We specify a two-equation model linking the quantity demanded of new firearms $q_{c,s,t}$ by class c in state s during year t, to the contemporaneous firearm stock $Q_{c,s,t}$ and corresponding homicide flow $d_{c,s,t}$:

$$\begin{aligned} &\text{(Gun stock law of motion)} \qquad && Q_{c,s,t} = (1-\varphi)Q_{c,s,t-1} + q_{c,s,t} \\ &\text{(Distribution of gun homicides)} \qquad && d_{c,s,t} \sim \text{Poisson}(Q_{c,s,t}^{\kappa_c}\zeta_{s,t}) \end{aligned}$$

The first equation of our model specifies the law of motion for the firearm stock by class, $Q_{c,s,t}$, accounting for the durable nature of firearms. Each year t, a uniformly random fraction $\varphi \in (0,1)$ of firearms degrade and exit circulation, while a fraction $1-\varphi$ persist. An additional flow of new firearms $q_{c,s,t}$ is added, from the quantity demanded in the contemporaneous legal firearms market. This law of motion captures that, even if the U.S. were to ban the sales of new firearms altogether, firearm ownership would persist, due to the large stock of existing firearms. We treat the existing firearm stock in 2015 $Q_{c,s,2015}$ as an initial condition to be calibrated from data, and use predictions from our model of the firearm market to determine the stock and flow of new firearms $q_{c,s,t}$ each year from 2016-2022.[29]

The second equation models firearm homicides $d_{c,s,t}$ as a Poisson random variable with expectation $Q_{c,s,t}^{\kappa_c}\zeta_{s,t}$, independently by class-state-year. This functional form matches the existing literature, in specifying a constant-elasticity relationship between firearm homicides $d_{c,s,t}$ and the contemporaneous firearm stock $Q_{c,s,t}$ (Duggan 2001, Azrael et al. 2004, Cook and Ludwig 2006, Kim and Wilbur 2022). Notably, the elasticity parameter κ_c varies by firearm class c, motivated by the literature linking firearm characteristics to the likelihood that a shooting results in death (Libby and Corzine 2007, Braga and Cook 2018, Braga et al. 2021). The remaining term $\zeta_{s,t}$ is an unobserved state-year homicide shock, capturing other other determinants of expected firearm homicides across markets (e.g., differences in criminal justice policy).

[29] We implicitly assume that used guns captured by the composite good are already counted in the firearms stock.

The above model provides a useful mapping between the firearm market and firearm homicides. Specifically, if there were exogenously $q'_{c,s,t}$ firearm purchases in a class-state-year, rather than $q_{c,s,t}$, then firearm homicides would change by

$$d'_{c,s,t} - d_{c,s,t} = d_{c,s,t} \times \left(\left(\frac{q'_{c,s,t} + (1-\varphi)Q_{c,s,t-1}}{q_{c,s,t} + (1-\varphi)Q_{c,s,t-1}} \right)^{\kappa_c} - 1 \right), \tag{13}$$

where the firearm homicide shocks $\zeta_{s,t}$ are absorbed into the status quo outcome $d_{c,s,t}$.

6.2 Calibration

We calibrate the parameters in Equation (13) using measurements from the existing literature, with calibration targets and parameter estimates summarized in Table 4.

Our calibration of the initial firearm stock $Q_{c,s,2015}$ combines information from the 2015 ACS, predictions of firearm ownership per capita from Schell et al. (2020), and microdata from the 2015 National Firearm Survey (Azrael et al. 2017), described in detail in Appendix OA.4.

To calibrate the degradation of firearms from the stock φ, we use existing estimates of the national firearm stock from two distinct points in time and the flow of new firearms over the intervening periods. Across the U.S., there were $Q_{1994} = 192$M firearms in 1994 and $Q_{2015} = 265$M firearms in 2015 (Cook and Ludwig 1996, Azrael et al. 2017). Each intervening year from 1995–2015, there was an inflow of q_t new firearms, equal to the ATF's measure of new firearms produced in the U.S., less net exports. Following Azrael et al. (2017), we compute the value of φ that satisfies our assumed law of motion given these data:

$$Q_{2015} = (1-\varphi)^{2015-1994} Q_{1994} + \sum_{t=1995}^{2015} (1-\varphi)^{2015-t} q_t,$$

This procedure leads to a calibrated value of $\varphi = 0.015$. Although less-likely to be scrapped than other consumer durables (Jacobsen and Van Benthem 2015), our calibrated rate of degradation for firearms φ is somewhat higher than found in prior studies (Moody 2010, Azrael et al. 2017, McDougal et al. 2023).

Turning to health, our calibration captures the average relationship between firearms and homicides, by matching existing estimates of the elasticity of firearm homicides with respect to the overall firearm stock, approximately 0.294.[30] As these existing estimates do

[30] Cook and Ludwig (2006) estimates an elasticity of 0.272, using the fraction of suicides committed by guns as a proxy measure. Duggan (2001) estimates a very similar elasticity of 0.316 using subscriptions to *Guns and Ammo* as a proxy measure for gun prevalence. We take the average of these two estimates.

not distinguish between firearms of different classes, we calibrate the total derivative of our model's homicide function (in logs):

$$0.294 = D\log(E[d_{s,t}]) = \kappa_h E[d_{h,s,t}/d_{s,t}] + \kappa_l E[d_{l,s,t}/d_{s,t}].$$

The right-hand expression is a convex combination of the class-specific elasticities, with weights equal to the share of firearm homicides committed with handguns and long guns.[31] As the shares of firearm homicides committed by handguns and long guns are observable in vital statistics—described in Appendix OA.4—this equation provides one moment governing the average of two unknown elasticities (κ_h and κ_l).

To capture the difference between the elasticity of homicides with respect to the handgun and long gun stocks—κ_h and κ_l—we match the shares of firearm homicides committed by handguns and long guns. Specifically, as 90 percent of firearm homicides during our sample are committed with a handgun, according to NVDRS, we require that

$$0.9 = \sum_{t=2016}^{2022} \sum_{s} \frac{d_{s,t}}{\sum_{t'=2016}^{2022} d_{t'}} E_{s,t}\left[\frac{d_{h,s,t}}{d_{s,t}}\right] = \sum_{s} \sum_{t} \frac{d_{s,t}}{\sum_{t'=2016}^{2022} d_{t'}} \frac{Q_{h,s,t}^{\kappa_h}}{Q_{h,s,t}^{\kappa_c} + Q_{l,s,t}^{\kappa_l}}.$$

The first term inside the summation is a weight, proportional to the total number of firearm fatalities in each state-year, recorded in the CDC vital statistics. The second term is the expected share of firearm homicides for which a handgun is responsible, which can either be observed in the NVDRS records or evaluated by iterating expectations under the model.[32]

Matching these two moments—governing the mean and difference between homicide elasticities κ_c—we find that firearm homicides are twice as elastic to the handgun stock as the long gun stock, with $\kappa_h = 0.309$ and $\kappa_l = 0.164$. Consistent with prior evidence, handguns are meaningfully larger determinants of firearm homicides than long guns (Libby and Corzine 2007). For instance, a *ceterus paribus* decrease in handgun homicides by 5% could be achieved through a $100 \times (1 - (1 - .05)^{\kappa_h}) \approx 15\%$ reduction in the handgun stock. While, achieving the same 5% reduction in long gun homicides would require a 26% reduction in the long gun stock.

[31] This relationship continues to hold if we match the elasticity of realized firearm homicides, instead of expected firearm homicides. This is because the purely idiosyncratic Poisson error cancels out when taking the ratio.

[32] Iterating expectations allows the firearm homicide shock $\zeta_{s,t}$ to cancel out of the ratio.

6.3 Results

Panel D of Table 4 shows the expected change in contemporaneous homicides from the sale of each new firearm in our sample. We compute these quantities by evaluating Equation (13) purchase-by-purchase, averaging over the distribution of new firearm purchases predicted by the model. The average handgun sale in the U.S. from 2016–2022 caused 3.57×10^{-5} firearm homicides during the year in which it was purchased. The average long gun sale over the same period caused 1.98×10^{-6} firearm homicides. Since handguns accounted for around 72% of new firearm sales over this period, the average firearm purchase in the U.S. caused 2.64×10^{-5} homicides during its first year in the firearm stock.

We find that firearms degrade from the stock at rate $\varphi = 0.015$ per year, so that the typical new firearm remains in circulation for $1/\varphi \approx 67$ years. Thus, our model implies that the average new firearm purchase in the U.S. from 2016–2022 would generate $2.64 \times 10^{-5} \times 67 \approx 0.0018$ homicides over its lifetime, or around 1 lifetime homicide for every 570 new firearm purchases.

We convert the lifetime homicide flows from a new firearm purchase into dollars of net present expected value under two further calibrations. Specifically, we impose a yearly discount factor of 0.95 and a statistical value of a life equal to \$9.5M (Peterson et al. 2021). Under these assumptions, the average new firearm purchased between 2016–2022 generates \$3,903 of present-day harm from its lifetime homicide flows.

Figure 3 compares the homicide costs of firearm purchase between handguns and long guns, and to the surplus generated for industry participants. The typical sale of one more handgun from 2016–2022 would generate around \$330 of damage from firearm homicides in its first year of circulation. Although smaller in magnitude than total market surplus, this one-year homicide cost is 15% higher than the surplus to the consumer of the handgun. However, the market surplus of \$700 from the typical new handgun purchase is dwarfed by its net present value of expected homicide fatalities, equal to \$5,040. Notably, the purchase of a new long gun generates surplus across the industry—and to its consumer—in excess of its net present homicide costs.

Our model demonstrates that the homicide costs of a new firearm purchase have less heterogeneity within models of the same class, than between firearm classes. At the 75th percentile, the purchase of a new handgun generates homicide costs around 25% larger than at the 25th percentile. Yet, the purchase of the average new handgun generates homicide costs around 2,600% larger than the typical long gun. These patterns of heterogeneity speak to the ability of regulators to improve welfare with the design of targeted firearm regulation, which we explore in the following section.

7 Counterfactuals

This section combines our fitted models of the firearm industry and firearm homicides from Sections 5 and 6—embedding them into the optimal tax model of Section 2—to study the design of alternate firearm regulation in the U.S.

7.1 Policies, Implementation, and Interpretation

We consider counterfactual changes in the federal excise tax on the sales of new firearms from manufacturers v_j. Each counterfactual can be represented by the vector of tax changes $\Delta\vec{v}$ of length $|\cup_{t=2016}^{2022} \mathcal{J}_t|$. The status quo of a 10% tax on handguns and an 11% tax on long guns is implemented by $\Delta\vec{v} = \vec{0}$.

Our analysis implements three progressively complex counterfactual tax changes $\Delta\vec{v}$. The first is a uniform tax increase of 11 percentage points across all firearms $\Delta\vec{v} = 0.11$, such that the tax rate on handguns is 21% and on long guns is 22%. This counterfactual scales up certain proposals and implementations of state-level firearm tax policies to the whole of the U.S. (Brownlee 2024), particularly California AB 28, which implemented the same tax increase in 2024 in California.[33]

We also consider a simplified implementation of the consumer surplus-constrained optimal taxes of Section 2, allowing only a "tilt" of the observed tax schedule facing handguns and long guns. Specifically, we allow the tax change to vary heterogeneously only across handguns Δv_h and long guns Δv_l, with all firearms in the same class c constrained to the same tax change. Since we do not develop optimal tax results for an environment with constrained tax instruments, our implementation of this counterfactual involves numerically solving the constrained optimization in Equation (2) over the two-dimensional space of class-specific tax changes $(\Delta v_h, \Delta v_l)$. In solving this problem, we also impose that neither tax change can lead to a net subsidy $-\Delta v_c \leq v_c$. We refer to this as a uniform handgun tax, as it involves raising the handgun tax as high as possible (15.5%), while setting the tax on long guns, which generate little public health externalities, to zero..

Our most complex counterfactual implements an approximation to full solution of the planner's problem in Equation (2), allowing a separate tax change on every firearm. We solve for these taxes by computing the constrained optimal tax formula in Equation (3) about the solution to the uniform handgun tax. This is a first-order approximation because we hold the taxes constant—as firms re-optimize their prices in response to the tax change $\Delta\vec{v}$—even though this alters the terms in Equation (3). Appendix OA.5 provides further

[33]See this link for the legislation: https://legiscan.com/CA/text/AB28/id/2842856

details. In practice, this scheme imposes zero taxes on long guns, but heterogeneous tax rates by handgun model, so we refer to it as the targeted handgun tax.

For each counterfactual, we simulate a change in the tax rates on new firearm sales from 2016–2022 by $\Delta\vec{v}$, and trace its effects on firearm pricing, purchase, ownership, and homicides. Prices adjust, as firearm producers re-optimize to maximize profits under the tax change $\Delta\vec{v}$, facing the same demand system, ownership matrix, marginal costs, used-firearm values $\omega_{c,s,t}$, and Nash-Bertrand pricing conditions we recover in Section 5. Facing different prices, consumers adjust their firearm purchases, which alters the profits, federal tax revenues, and consumer surplus from the industry. The change in firearm purchases also affects firearm homicides—as in Equation (13)—because the tax change $\Delta\vec{v}$ adjusts the endogenous evolution of the firearm stock.

We measure the welfare effects of a counterfactual tax change $\Delta\mathcal{W}(\Delta\vec{v})$ by its component effects on consumer surplus, profits, federal government revenue, and homicide externalities, as in Equation (1). For each counterfactual, we report the change in welfare relative to the status quo from 2016–2022:

$$\Delta\mathcal{W}(\Delta\vec{v}) \equiv \sum_{t=2016}^{2022} \mathcal{W}_t(\Delta\vec{v}) - \mathcal{W}_t(\vec{0}),$$

where the change in each welfare component is defined analogously. Section OA.5 provides explicit expressions.

Unlike our analysis of the observed equilibrium in Sections 4–6, our analysis of welfare from counterfactual taxes $\Delta\vec{v}$ involves both extrapolating beyond the observed data and assigning normative interpretations to our model, both of which limit the reliability of our results. In extrapolating, our counterfactuals allow only adjustments to the prices and quantities of legal firearms already available to consumers, holding fixed large components of the firearms industry. Specifically, we do not allow for the possibility that a tax change may affect the innovation of new firearm models, the equilibrium of the illicit firearm market,[34] the behavior of firearm retailers, or the valuations of used firearms.[35] Among the normative

[34]Existing work suggests minimal consumer substitution between the licit and illicit firearm markets, with three-times higher prices through illicit sales channels (Cook et al. 2007). The price changes we study in our counterfactuals are much smaller in magnitude, giving us some confidence in our extrapolation.

[35]We match the structure of current federal firearm tax policies by assessing counterfactual taxes only on the sale of new (not used) firearms. Our assumption that the value of used firearms $u_{i,\omega_c,s,t}$ is invariant to the tax change $\Delta\vec{v}$ is a substantive restriction on demand (i.e., consumers do not internalize that their purchase of new firearms can be resold tax-free) and supply (i.e., manufacturers do not internalize that their sale of new firearms in t may increase the supply of used firearms in future period t'). This assumption would be satisfied if used firearms were supplied at-cost by a competitive fringe, making zero economic profits. We view this as a reasonable assumption: there were hundreds of millions of used firearms in circulation across the U.S. during our sample period, which could be bought and sold by tens of thousands of licensed,

interpretations we impose, several key ones are that only federal tax revenues enter welfare,[36] that marginal costs of production are a pure welfare loss,[37] and that the only externality from firearm purchase is statistical value of firearm homicides.[38] We view these caveats as necessary to appropriately interpret our predictions of the effects of counterfactual tax changes $\Delta\vec{v}$. At the same time, our choice to focus on tax changes that keep consumer surplus constant naturally limits the degree of changes we impose on the firearms market, which mitigates concerns about extrapolation.

7.2 Counterfactual Results

Panel (a) of Figure 4 plots the average annual change in welfare from 2016–2022 for each of the counterfactual taxes $\Delta\vec{v}$ we consider. Our simplest counterfactual—effectively doubling the existing tax rate to 21% on handguns and 22% on long guns—improves overall welfare by 280M$ per year during our sample. The gains are achieved in roughly equal proportion through a \$770M increase in federal tax revenue and the prevention of 76 firearm homicides each year. However, simply doubling the tax rate on firearms considerably harms direct market participants, destroying \$640M of yearly consumer surplus and \$590M of yearly manufacturer profits.

In contrast, our uniform handgun tax achieves superior overall welfare gains, while minimizing harm on consumers and firms. Despite lowering the average tax rate, tilting the tax increases welfare 37% more than doubling the tax, as the tilted-tax better differentiates rates across firearms. This aligns the tax scheme with the results in Figure 3, which show that handgun purchases generate considerably less social surplus than long gun purchases. Although surplus from the market is unchanged, the tilted-tax policy targets the products (handguns) that generate the worse negative externalities, preventing 40 firearm homicides each year, relative to the current equilibrium.

Our most sophisticated counterfactual implements the constrained-optimal tax of Section 2, generating a further 32% increase in in-sample welfare relative to the unfiorm handgun tax. Panel (a) of Figure 5 shows that this welfare gain comes from further differentiating tax rates across handguns (SD=5 percentage points), with rates from 0%–26%. Panels (b)-(d) provide

brick-and-mortar suppliers (Azrael et al. 2017, Johnson and Robinson 2021).

[36]Firearm purchases also generate tax revenue for state and local governments through sales taxes and licensing fees, absent from our model.

[37]Marginal costs may include worker wages or transfers to downstream distributors, both of which may also generate social welfare.

[38]Firearms are also used in non-lethal crime. Though past studies have found smaller effects of the firearm stock on non-fatal crimes (Duggan 2001, Rosenberg 2024). We also do not account for any effects of the firearm stock on incidents of self-harm, nor on broader externalities like social well-being, mental health, or schooling (Pienkny et al. 2024, Cabral et al. 2021).

information on the sort of handgun models that are taxed more. Handguns that produce less value for consumers (Panel b) are taxed more, as measured by the average consumer surplus from each purchase at baseline. Panel (c) shows that this coincides with handguns that are cheaper to produce ("Saturday night specials"). This revised tax scheme therefore relaxes the consumer surplus constraint, allowing a 6% higher tax rate on the average handgun model than under the targeted handgun tax policy (16.4% versus 15.5%). Handguns more likely to be purchased by consumers with weaker preferences towards specific products, and therefore more likely to substitute to alternatives, such as a used handgun, or no gun at all, are taxed at higher rates. Panel (d) shows that the this tax design translates to larger price increases on handguns that divert more of their consumer base towards these less-harmful choices.[39] Roughly, the constrained-optimal firearm tax policy subsidizes the inframarginal purchases of new handguns, in order to target taxes at consumers who may be deterred from new handguns on the margin. Through this mechanism, the targeted handgun tax reduces the flow of new firearms into circulation, preventing 50 firearm homicides each year, while also increasing tax revenue at the cost of some manufacturer profits.

Since the typical firearm endures in circulation for 67 years, the effects of a policy in the average year between 2016–2022 may mask its long term benefits over time. Without extrapolating into the future, Panel (b) of Figure 4 plots the annual accumulated effect of each policy on social welfare. Each policy improves over time, as the stock of socially harmful firearms continually recedes. After 7 years, simply doubling the tax rate on firearms is the best-performing policy, in terms of overall welfare, highlighting that higher firearm taxes may produce substantial welfare gains through homicide reduction over the long-run. Yet, the durability of firearms leads the benefits from homicide reduction to accrue slowly over time—while losses in market surplus are immediate—and doubling the firearm tax lowers social welfare during its first two years of implementation. Our constrained handgun tax policies lead to lower taxes and immediate gains in social welfare, which may further aid their political feasibility given that the short-term political cycles often motivate policy (Bonfiglioli and Gancia 2013).

Figure OA.20 shows how market power in the firearm industry determines the effects of tax changes $\Delta\vec{v}$ on equilibrium prices and quantities. Market power leads to undershifting, with only about 60% of the tax change on manufacturers being passed through to the prices facing consumers. Under our maintained assumption Nash-Bertrand competition, doubling the tax rate would reduce the quantity of firearm purchases by 360,000 units per year. In contrast, the constrained taxes we study lead to 80% smaller net changes in firearm purchases, but instead shift the composition of firearm purchases towards long guns and

[39]Measured as the diversion ratio towards distinct gun types at the current equilibrium.

used handguns, and away from new handguns. The constrained-optimal firearm tax induces a further shift in the composition among new handgun purchases, as it generates highly-dispersed equilibrium prices, with many firms decreasing the prices of some handgun models. Figure OA.21 shows that the (erroneous) assumption of perfect competition and full pass-through of the tax change to prices would produce welfare estimates that were incorrect by an order of magnitude and produce an incorrect ranking of counterfactual tax policies.[40]

We also consider firearm regulation through an increase in market power, with Figure OA.22 showing the welfare effects of counterfactually shifting to the multi-product monopoly markups that would obtain under full price coordination. This counterfactual is motivated both by theory—Buchanan (1969) argues that monopoly power may correct externalities without regulatory intervention—and by the legal structure of the U.S. Master Settlement Agreement in the tobacco industry (Bulow and Klemperer 1998, Cutler et al. 2002). Full monopolization of firearm manufacturing would generate an increase in prices, a decrease in quantities, and a sufficient increase in market revenue to both improve manufacturer profits and increase federal tax revenues (through a lump-sum transfer). We estimate that the decrease in new firearm purchase quantities from monopolization would prevent 400 homicides in the average year between 2016–2022, the largest of any policy we consider. Full monopolization would also harm consumers: their annual surplus would fall by \$2.3B, destroying nearly 10% of the consumer surplus generated by the current firearms industry. The large decline in consumer surplus suggests that consumer advocacy groups, who wield significant political power in our setting, would oppose such a policy intervention and render it politically infeasible.

We motivated our constrained optimal tax problem in Section 2 through a discussion of the role that firearm owners (and their advocacy organizations) play in federal policy. National surveys find that firearm ownership is twice as common among Republicans as Democrats (Parker et al. 2017), and our analysis reveals that firearm purchasing is more likely in conservative areas of Massachusetts and that consumers in areas with more NRA donations. Insofar as our tax counterfactuals are politically feasible, they would require support from Republican legislators at the national level, which in turn may depend on how the tax would affect their constituents.

Figure 6 examines political feasibility by directly plotting the welfare effects of each counterfactual tax against the Republican vote share in the 2016 Presidential Election, state-by-state. Our measure of state-level welfare ("population surplus") includes only consumer

[40] Explicitly, we assume firms set $p_{j,t}(1 - v_{j,t}) = c_{j,t}$ and make zero economic profits. For these policy exercises, we re-solve for the uniform and targeted handgun taxes that set consumer surplus equal to zero, and use an optimal targeted tax based on Proposition 3 in Appendix OA.1.

surplus and homicides, to represent that these are benefits accrue directly to the state population.

In Panel (a), we plot the effects of doubling federal firearm tax in each state. This tax change destroys the most consumer surplus among individuals with the highest willingness to pay for firearms—disproportionately Republican voters—even as decreases in homicide fatalities occur across the political spectrum. As such, population surplus is inversely correlated with Republican vote share, such that the states most harmed by the firearm tax increase are those with the highest Republican vote share. California, where the state government doubled the firearms excise tax in 2024, unsurprisingly experiences a net benefit from this policy change. However, 29 states experience a net loss in population surplus, underscoring the political challenges of passing a broad scale increase in firearm taxes at the national level.

In Panels (b) and (c), we plot the welfare effects of the tilted and constrained-optimal firearm taxes across states, both of which induce similar profiles. While aggregate consumer surplus is unchanged, by construction, these targeted policies also induce minimal correlation between consumer surplus and Republican vote share. In fact, we estimate a slight increase in consumer surplus in the most Republican states, as consumers in these areas have a disproportionate taste for long guns (with counterfactually zero tax) than for handguns (with counterfactually higher tax). Figure OA.23, replicates this pattern across congressional districts with different levels of NRA donations per capita. Republican states also benefit much more in terms of population surplus, due to a substitution effect. As consumers in conservative neighborhoods have higher preferences for long guns, taxes targeted at handguns are able to induce more substitution to long guns in Republican states, without harming many politically conservative consumers. These forces lead to reductions in homicide at no systematic cost to consumer surplus across the political spectrum. Moreover, every state experiences a net gain in population surplus from each targeted policy, with slightly larger gains under the constrained-optimal tax.

From our analysis of counterfactual firearm regulations, the tilted-tax redesign appears as a potentially strong policy option. It holds constant consumer surplus, manufacturer profits, and federal revenues, while saving dozens of lives each year. By adjusting only two preexisting federal rates, the tilted-tax is simple to explain and to codify in law. Yet it achieves around 80% of the welfare gain from the theoretically constrained-optimal tax, that assigns unique tax rates to each handgun model each year. Perhaps most importantly, this tax change does no systematic harm to consumers across the political spectrum, while providing disproportionate public health benefits to Republican- and NRA-supporting areas. As such, we view the tilted-tax on federal firearms as a politically palatable improvement over the existing taxes in the consumer firearms industry.

8 Conclusion

In this paper, we provide estimates of supply and demand for the U.S. consumer firearm industry that are based on observed firearm transactions and the prices facing consumers. Through descriptive analysis and a structural model, we show that firearm consumers are moderately price elastic, that demographics are a substantial input into preferences over the characteristic space of firearms, and that substitution across firearm classes is relatively low. We estimate that market power plays a significant role in the supply side of the firearms market, leading to large markups and incomplete pass-through of taxes to consumers, which meaningfully impacts the welfare implications of alternative policies. In order to benchmark the effect of changes to market outcomes on firearms externalities, we calibrate a stylized model of public health. In our counterfactual policy exercises, we show that targeted taxes on handguns are more welfare enhancing than uniform taxes, primarily because of the distinct social costs across firearms. Moreover, these targeted policies have properties that may make them politically feasible: gun consumers on net do not lose surplus, and the largest beneficiaries are those living in conservative states, which historically have been a barrier to new firearms legislation.

While our paper is a step towards understanding this market, many questions are left unanswered. This paper does not speak to potential regulation on the illicit market for firearms, and how this may respond to changes in government policy. The dynamics of the gun market are not explicitly modeled, though we show that these dynamics are important for understanding the public health benefits, because guns are highly durable goods. Finally, this paper cannot speak to larger-scale reforms of firearms regulation, such as universal buyback programs or bans on certain types of firearms. Much of this is due to the limitations facing researchers on assembling data about the firearms industry. Our hope is that further work on this topic can aid both researchers and policymakers in understanding the consequences of firearms regulation when accounting for the market structure of this industry.

References

Hunt Allcott, Benjamin B Lockwood, and Dmitry Taubinsky. Regressive sin taxes, with an application to the optimal soda tax. *The Quarterly Journal of Economics*, 134(3): 1557–1626, 2019.

Dmitry Arkhangelsky, Susan Athey, David A Hirshberg, Guido W Imbens, and Stefan Wager. Synthetic difference-in-differences. *American Economic Review*, 111(12):4088–4118, 2021.

Luis Armona and Adam M Rosenberg. Measuring the market for legal firearms. In *AEA Papers and Proceedings*, volume 114, pages 52–57. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, 2024.

Deborah Azrael, Philip J Cook, and Matthew Miller. State and local prevalence of firearms ownership measurement, structure, and trends. *Journal of Quantitative Criminology*, 20: 43–62, 2004.

Deborah Azrael, Lisa Hepburn, David Hemenway, and Matthew Miller. The stock and flow of us firearms: results from the 2015 national firearms survey. *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 3(5):38–57, 2017.

Matthew Backus, Christopher Conlon, and Michael Sinkinson. Common ownership and competition in the ready-to-eat cereal industry. Technical report, National Bureau of Economic Research, 2021.

Meenakshi Balakrishna and Kenneth C Wilbur. Do firearm markets comply with firearm restrictions? how the massachusetts assault weapons ban enforcement notice changed registered firearm sales. *Journal of empirical legal studies*, 19(1):60–89, 2022.

Panle Jia Barwick, Hyuk-soo Kwon, and Shanjun Li. Attribute-based subsidies and market power: an application to electric vehicles. 2023.

Alexandre Belloni, Daniel Chen, Victor Chernozhukov, and Christian Hansen. Sparse models and methods for optimal instruments with an application to eminent domain. *Econometrica*, 80(6):2369–2429, 2012.

John Berrigan, Deborah Azrael, and Matthew Miller. The number and type of private firearms in the united states. *The ANNALS of the American Academy of Political and Social Science*, 704(1):70–90, 2022.

Steven Berry, James Levinsohn, and Ariel Pakes. Automobile prices in market equilibrium. *Econometrica*, 63(4):841–890, 1995.

Steven T Berry and Philip A Haile. Foundations of demand estimation. In *Handbook of industrial organization*, volume 4, pages 1–62. Elsevier, 2021.

Douglas C Bice and David D Hemley. The market for new handguns: an empirical investigation. *The Journal of Law and Economics*, 45(1):251–265, 2002.

Frederick J Boehmke, Sean Gailmard, and John W Patty. Business as usual: interest group access and representation across policy-making venues. *Journal of Public Policy*, 33(1): 3–33, 2013.

Katie Bollman, Benjamin Hansen, Edward A. Rubin, and Garrett O. Stanford. Gun policy and the steel paradox: Evidence from oregunians. Technical report, National Bureau of Economic Research, 2025.

Alessandra Bonfiglioli and Gino Gancia. Uncertainty, electoral incentives and political myopia. *The Economic Journal*, 123(568):373–400, 2013.

Anthony A Braga and Philip J Cook. The association of firearm caliber with likelihood of death from gunshot injury in criminal assaults. *JAMA network open*, 1(3):e180833–e180833, 2018.

Anthony A Braga and David M Hureau. Strong gun laws are not enough: the need for improved enforcement of secondhand gun transfer laws in massachusetts. *Preventive medicine*, 79:37–42, 2015.

Anthony A Braga, Elizabeth Griffiths, Keller Sheppard, and Stephen Douglas. Firearm instrumentality: do guns make violent situations more lethal? *Annual Review of Criminology*, 4(1):147–164, 2021.

Jurgen Brauer. The us firearms industry: Production and supply. *Small Arms Survey Working Paper 14*, 2013.

Randy Brenkers and Frank Verboven. Liberalizing a distribution system: The european car market. *Journal of the European Economic Association*, 4(1):216–251, 2006.

Chip Brownlee. Seven states move to tax guns and ammo. 2024.

James M Buchanan. External diseconomies, corrective taxes, and market structure. *The American Economic Review*, 59(1):174–177, 1969.

Jeremy Bulow and Paul Klemperer. The tobacco deal. *Brookings Papers on Economic Activity. Microeconomics*, 1998:323–394, 1998.

Marika Cabral, Bokyung Kim, Maya Rossin-Slater, Molly Schnell, and Hannes Schwandt. Trauma at school: The impacts of shootings on students' human capital and economic outcomes. Technical report, National Bureau of Economic Research, 2021.

N Scott Cardell. Variance components structures for the extreme-value and logistic distributions with application to models of heterogeneity. *Econometric Theory*, 13(2):185–213, 1997.

Matias D Cattaneo, Richard K Crump, Max H Farrell, and Yingjie Feng. On binscatter. *arXiv preprint arXiv:1902.09608*, 2019.

Congressional Research Service. Firearms and ammunition excise tax (faet). 2023.

Christopher Conlon and Jeff Gortmaker. Best practices for differentiated products demand estimation with pyblp. *The RAND Journal of Economics*, 51(4):1108–1161, 2020.

Christopher Conlon and Nirupama L Rao. The cost of curbing externalities with market power: Alcohol regulations and tax alternatives. Technical report, National Bureau of Economic Research, 2023.

Philip J Cook and Jens Ludwig. *Guns in America: results of a comprehensive national survey on firearms ownership and use*. Police Foundation Washington, DC, 1996.

Philip J Cook and Jens Ludwig. The social costs of gun ownership. *Journal of Public Economics*, 90(1-2):379–391, 2006.

Philip J Cook, Jens Ludwig, Sudhir Venkatesh, and Anthony A Braga. Underground gun markets. *The Economic Journal*, 117(524):F588–F618, 2007.

David M Cutler, Jonathan Gruber, Raymond S Hartman, Mary Beth Landrum, Joseph P Newhouse, and Meredith B Rosenthal. The economic impacts of the tobacco settlement. *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management*, 21(1):1–19, 2002.

Peter A Diamond. Consumption externalities and imperfect corrective pricing. *The Bell Journal of Economics and Management Science*, pages 526–538, 1973.

Mark Duggan. More guns, more crime. *Journal of political Economy*, 109(5):1086–1114, 2001.

Amit Gandhi and Jean-François Houde. Measuring substitution patterns in differentiated-products industries. *NBER Working paper*, (w26375), 2019.

Amit Gandhi and Aviv Nevo. Empirical models of demand and supply in differentiated products industries. In *Handbook of industrial organization*, volume 4, pages 63–139. Elsevier, 2021.

Matthew Gentzkow, Jesse M Shapiro, and Matt Taddy. Measuring group differences in high-dimensional choices: method and application to congressional speech. *Econometrica*, 87 (4):1307–1340, 2019.

Austan Goolsbee and Amil Petrin. The consumer gains from direct broadcast satellites and the competition with cable tv. *Econometrica*, 72(2):351–381, 2004.

Paul LE Grieco, Charles Murry, and Ali Yurukoglu. The evolution of market power in the us automobile industry. *The Quarterly Journal of Economics*, page qjad047, 2023.

Niklas Hüther. More guns lead to more crime: Evidence from private equity deals. *Mimeo*, 2023.

Janice Iwama and Jack McDevitt. Rising gun sales in the wake of mass shootings and gun legislation. *Journal of Primary Prevention*, 42:27–42, 2021.

Mark R Jacobsen and Arthur A Van Benthem. Vehicle scrappage and gasoline policy. *American Economic Review*, 105(3):1312–1338, 2015.

David B. Johnson, Joshua J. Robinson, Daniel Semenaza, and Alexi Thompson. Where are the guns? Technical report, 2023. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4119613.

David Blake Johnson and Joshua J Robinson. Gun dealer density and its effect on homicide. *Available at SSRN 3867782*, 2021.

Vlad Khaustovich. Guns and ammunition manufacturing in the us. Technical report, IBIS-World, 2025.

Jessica Jumee Kim and Kenneth C Wilbur. Proxies for legal firearm prevalence. *Quantitative Marketing and Economics*, 20(3):239–273, 2022.

Brian Knight. State gun policy and cross-state externalities: Evidence from crime gun tracing. *American Economic Journal: Economic Policy*, 5(4):200–229, 2013.

Christopher S Koper and Jeffrey A Roth. The impact of the 1994 federal assault weapons ban on gun markets: An assessment of short-term primary and secondary market effects. *Journal of quantitative criminology*, 18(3):239–266, 2002.

Matthew J Lacombe. *Firepower: How the NRA turned gun owners into a political force*. Princeton University Press, 2021.

Matthew Lang. State firearm sales and criminal activity: evidence from firearm background checks. *Southern Economic Journal*, 83(1):45–68, 2016.

Eulalie Laschever and David S Meyer. Growth and decline of opposing movements: Gun control and gun rights, 1945–2015. *Mobilization*, 26(1):1–20, 2021.

Nicholas E Libby and Jay Corzine. Lethal weapons: Effects of firearm types on the outcome of violent encounters. *Justice Research and Policy*, 9(2):113–137, 2007.

Michael Luca, Deepak Malhotra, and Christopher Poliquin. The impact of mass shootings on gun policy. *Journal of public economics*, 181:104083, 2020.

Gregory J Martin and Ali Yurukoglu. Bias in cable news: Persuasion and polarization. *American Economic Review*, 107(9):2565–2599, 2017.

Topher L McDougal, Daniel Montolio, and Jurgen Brauer. Modeling the us firearms market: the effects of civilian stocks, legislation, and crime. *International social science journal*, 2023.

Matthew Miller, Wilson Zhang, and Deborah Azrael. Firearm purchasing during the covid-19 pandemic: results from the 2021 national firearms survey. *Annals of Internal Medicine*, 175(2):219–225, 2022.

Nathan H Miller and Matthew C Weinberg. Understanding the price effects of the millercoors joint venture. *Econometrica*, 85(6):1763–1791, 2017.

Carlisle E Moody. Firearms and homicide. In *Handbook on the Economics of Crime*. Edward Elgar Publishing, 2010.

Terrence J Moore, Brian M Sadler, and Richard J Kozick. Maximum-likelihood estimation, the cramér–rao bound, and the method of scoring with parameter constraints. *IEEE Transactions on Signal Processing*, 56(3):895–908, 2008.

Sarah Moshary, Bradley T Shapiro, and Sara Drango. Preferences for firearms. *American Economic Review: Insights*, 7(3):340–356, 2025.

Aviv Nevo. Mergers with differentiated products: The case of the ready-to-eat cereal industry. *The RAND Journal of Economics*, pages 395–421, 2000.

Martin O'Connell and Kate Smith. Optimal sin taxation and market power. *American Economic Journal: Applied Economics*, 16(4):34–70, 2024.

Kim Parker, Juliana Menasce Horowitz, Ruth Igielnik, J Baxter Oliphant, and Anna Brown. The demographics of gun ownership. *Pew Research Center*, 22, 2017.

Cora Peterson, Gabrielle F Miller, Sarah Beth L Barnett, and Curtis Florence. Economic cost of injury—united states, 2019. *Morbidity and Mortality Weekly Report*, 70(48):1655, 2021.

Max Pienkny, Maya Rossin-Slater, Molly Schnell, and Hannes Schwandt. The lasting impacts of school shootings on youth psychotropic drug use. *AEA Papers and Proceedings*, 114:387–93, May 2024. doi: 10.1257/pandp.20241085. URL https://www.aeaweb.org/articles?id=10.1257/pandp.20241085.

Arthur Cecil Pigou. *The Economics of Welfare*. Macmillan, 1924.

Frank P Ramsey. A contribution to the theory of taxation. *The economic journal*, 37(145): 47–61, 1927.

RAND. The relationship between firearm prevalence and violent crime. Technical report, 2018. URL https://www.rand.org/research/gun-policy/analysis/essays/firearm-prevalence-violent-crime.html.

Adam Rosenberg. Regulating firearm markets: Evidence from california. 2024.

Terry L. Schell, Samuel Peterson, Brian G. Vegetabile, Adam Scherling, Rosanna Smart, and Andrew R. Morral. *State-Level Estimates of Household Firearm Ownership*. RAND Corporation, Santa Monica, CA, 2020. doi: 10.7249/TL354.

Rosanna Smart. Firearm and ammunition taxes. Technical report, 2021. URL https://www.rand.org/research/gun-policy/analysis/essays/firearm-and-ammunition-taxes.html.

Sierra Smucker, Max Griswold, Amanda Charbonneau, Rose Kerber, Terry L Schell, and Andrew R Morral. *Using National Instant Criminal Background Check Data for Gun Policy Analysis: A Discussion of Available Data and Their Limitations*. RAND, 2022.

Rebeccah L Sokol, Marc A Zimmerman, Laney Rupp, Justin E Heinze, Rebecca M Cunningham, and Patrick M Carter. Firearm purchasing during the beginning of the covid-19 pandemic in households with teens: a national study. *Journal of behavioral medicine*, 44: 874–882, 2021.

Marcella Alsan Joshua Schwartzstein Stefanie Stantcheva. The universal pursuit of safety and the demand for (lethal, non-lethal or no) guns. 2025.

Robert Tibshirani. Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 58(1):267–288, 1996.

Kenneth E Train. *Discrete choice methods with simulation*. Cambridge university press, 2009.

Frank Verboven. International price discrimination in the european car market. *The RAND Journal of Economics*, pages 240–268, 1996.

Berto Villas-Boas, Sofia. Vertical relationships between manufacturers and retailers: Inference with limited data. *The Review of Economic Studies*, 74(2):625–652, 2007.

Voting and Election Science Team. 2016 Precinct-Level Election Results, 2018. URL https://doi.org/10.7910/DVN/NH5S2I.

	(1) Adult Pop.	(2) Potential Gun Buyers	(3) Gun Buyers	(4) Handgun Buyers	(5) Longgun Buyers
Female	0.521	0.430	0.085	0.107	0.048
Fraction White in Zipcode	0.718	0.738	0.813	0.804	0.828
Poverty Rate in Zipcode	0.106	0.100	0.081	0.083	0.078
Conservative Vote Share (2016)	0.365	0.380	0.440	0.437	0.444
Density of Zipcode	1,940	1,677	666	712	587
Median Zipcode Income	87,263	87,715	88,528	88,031	89,381
Fraction BA+ in Zipcode	0.438	0.433	0.402	0.399	0.407

Table 1: Demographics of Gun Buyers in Massachusetts

Figure reports the average demographic characteristics of sub-populations in Massachusetts. Each row reports a particular gender-by-zipcode demographic cell, with the columns varying the weights used. Column (1) weights by the adult population in each cell, estimated from the 2015-2019 ACS. Column(2) weights by the predicted # of potential gun buyers (those who own or are willing to own a gun). Column (3) weights by the number of gun purchases in each cell from 2016-2022. Column (4) weights by the number of handgun purchases in each cell from 2016-2022. Column (5) weights by the number of long gun purchases in each cell from 2016-2022. Density is measured as total population per square mile.

Weapon Class:	Handguns		Long guns	
Aggregation:	Model-Years	Transactions	Model-Years	Transactions
	(1)	(2)	(3)	(4)
Caliber (Inches)	0.359	0.357	0.449	0.424
	(0.093)	(0.060)	(0.218)	(0.220)
Barrel Length (inches)	4.427	3.782	22.926	20.487
	(2.183)	(1.047)	(4.433)	(3.813)
High Capacity Weapon	0.167	0.293	0.135	0.261
	(0.373)	(0.455)	(0.341)	(0.439)
Shotgun	0.000	0.000	0.395	0.325
	(0.000)	(0.000)	(0.489)	(0.468)
In Active Production (New)	0.289	0.688	0.309	0.591
	(0.453)	(0.463)	(0.462)	(0.492)
MSRP (Cond. New, 2022$)	1124.065	829.800	2262.390	1066.369
	(804.209)	(632.686)	(5084.949)	(1317.415)
Number of Gun Models	2835		4781	
Number of Transactions/Year	815,241		461,776	

Table 2: Gun Characteristics summary statistics

Table shows the average characteristics of firearms in the Blue Book of Gun Values that are matched to models in the FRB Massachusetts transaction data (e.g. those purchases in Massachusetts from 2016-2022). MSRP is calculated only for those guns in active production during this period. Model-years denotes summary statistics along those available to Massachusetts consumers from 2016-2022, while Transactions denotes summary statistics, weighted by number of dealer purchases.

	(1) IHS(Purchases)	(2) IHS(Purchases)	(3) IHS(Purchases)
Log(MSRP)	-0.726**	-2.156**	-2.491***
	(0.331)	(0.858)	(0.828)
Observations	2457	2457	2457
Gun Model FE	Yes	Yes	Yes
Year FE	Year	Year	Class x Year
# Potential Instruments		3366	3366
# Selected Instruments		8	6
Sup-Score Test Statistic		12.43	12.55
First Stage Sig. (p-value)		0.0000	0.0000
Method	OLS	IVLASSO	IVLASSO

Table 3: Estimated Price Elasticity of Demand for Firearms

Table displays the estimated own-price elasticity of demand from the IVLASSO routine described in Section 4.1. The sample in this table is restricted to guns with at least 100 purchases in Massachusetts from 2016-2022. Column (1) reports the estimates from an OLS regression of IHS(# Purchases) on Log(MSRP), with gun model and year fixed effects. Columns (2) and (3) reports the estimates using the metals commodity cost shock variable as an instrument for MSRP, with year and weapon class by year fixed effects, respectively. Standard errors in parentheses are robust to heterogeneity. * denotes $p < .1$, ** denotes $p < .05$, *** denotes $p < .01$.

Object	Value	Source
Panel A: Firearm law of Motion		
Households$_{s,2015}$	———	2015 ACS, 5-year estimate
Pr(Adult has gun in HH)$_{s,2015}$	———	Schell et al. (2020)
Gun owners per HH with gun$_{2015}$	1.705	Azrael et al. (2017)
Guns per Gun Owner$_{c,s,2015}$	———	Azrael et al. (2017)
Degradation rate φ	0.015 (0.0042)	Cook and Ludwig (1996). Azrael et al. (2017), ATF firearms commerce report
Panel B: Public Health Target Outcomes		
Pr(Shot handgun | Gun homicide)	0.90	FBI Supplemental Homicide Reports, NVDRS
Elasticity of gun homicide wrt HH gun ownership	0.294	Duggan (2001), Cook and Ludwig (2006)
Panel C: Public Health Calibrated Parameters		
κ_h: Elasticity of gun homicide wrt handgun stock	0.309 (0.00032)	
κ_l: Elasticity of gun homicide wrt long gun stock	0.164 (0.0034)	
Welfare cost, 1 gun homicide	\$9.5m	Peterson et al. (2021)
Yearly discount factor	0.95	
Panel D: Average marginal homicides from firearm purchase		
Handgun	3.57×10^{-5}	
Long gun	1.98×10^{-6}	
Share handguns among purchases	0.72	
Average marginal homicides	2.64×10^{-5}	

Table 4: Calibration sources and parameter estimates for homicide model

Table displays data source, calibration targets, and parameter values from the model of firearm homicides in Section 6. Standard errors in parentheses are computed from the gradient of the calibration objective with respect to parameters, separately for the degradation rate φ and the homicide elasticities κ_c, as described in Appendix OA.4.

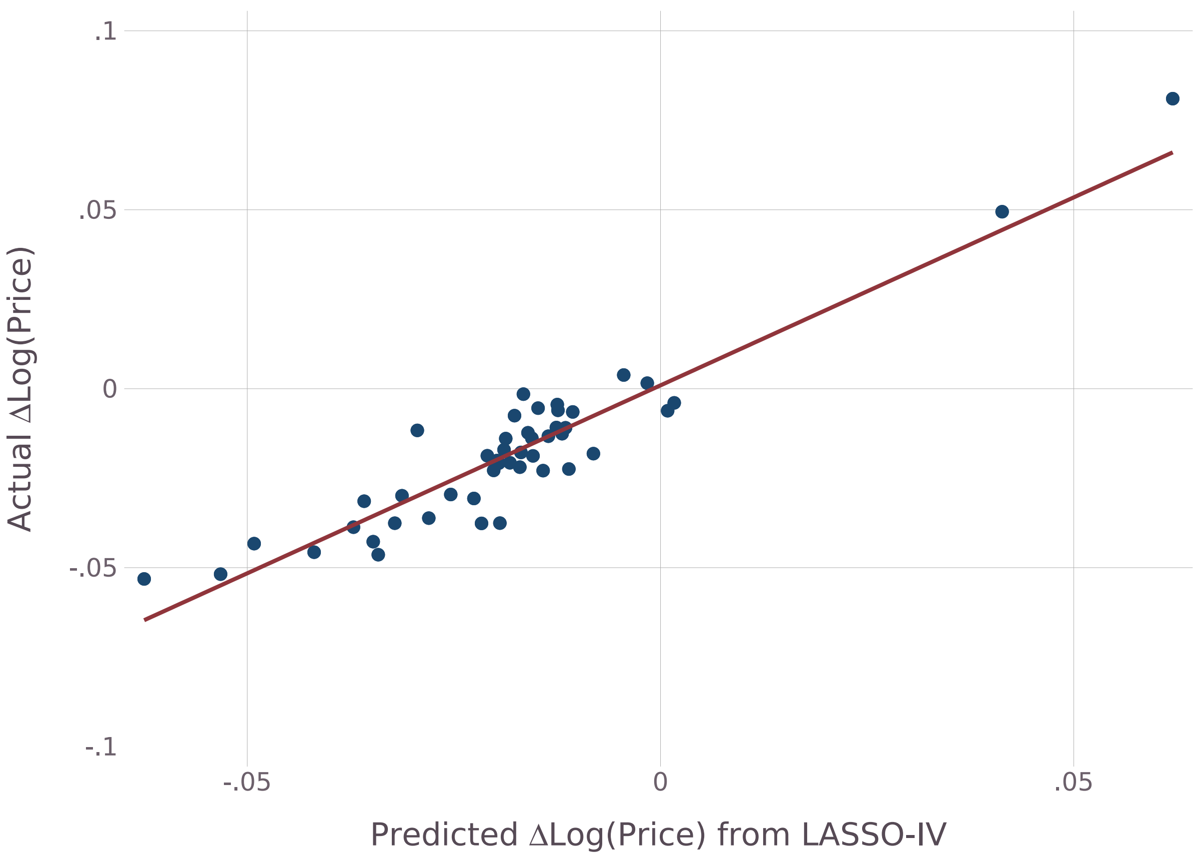
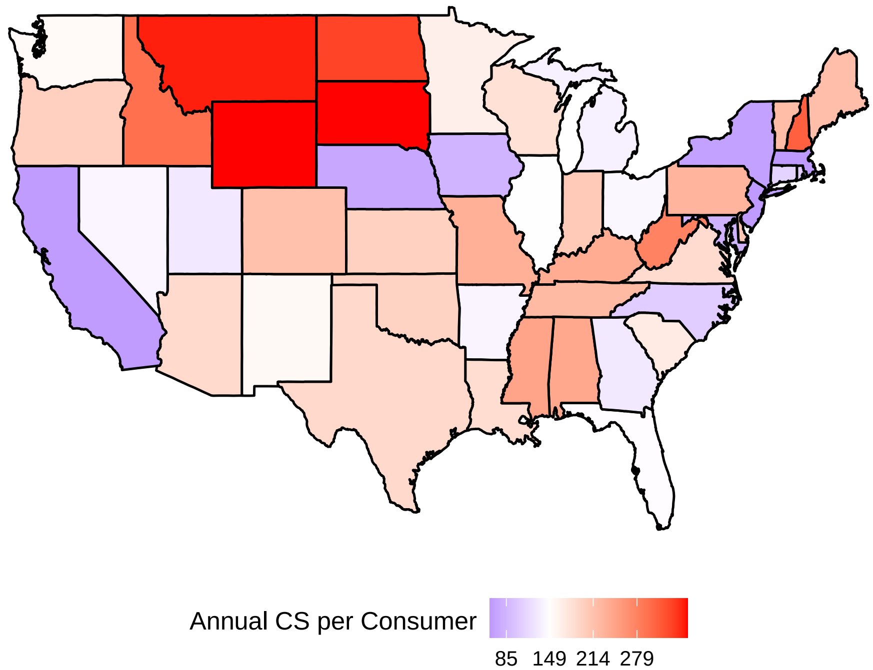
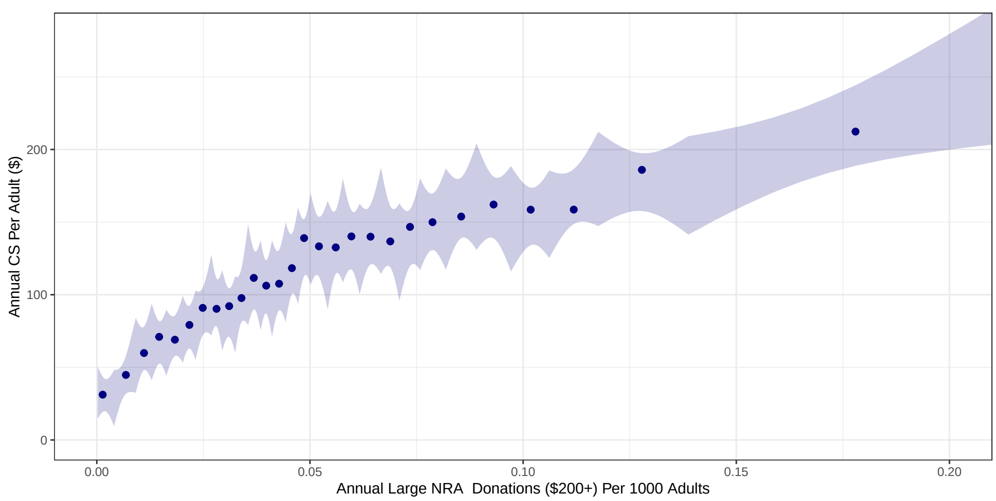


Figure 1: Binscatter of Predicted IVLASSO and Actual Prices

Note: Figure plots the binscatter of year-to-year changes in residualized predicted and actual MSRP, for gun models produced by manufacturers with non-zero coefficients.



(a) Consumer Surplus Across the U.S.



(b) Consumer Surplus Correlates with NRA Donations

Figure 2: Consumer Surplus from the Firearms market in the U.S.

Figure displays consumer surplus from the U.S. firearms industry. Panel (a) displays the annual dollar value of consumer surplus per adult in each state, averaged over 2016-2022. White represents the population-weighted mean consumer surplus per adult in the U.S. Scale ticks represent population-weighted standard deviations of consumer surplus per adult. Panel (b) displays a binscatter 95% confidence bands against the number of donations per 1,000 adults, using the procedure of Cattaneo et al. (2019)

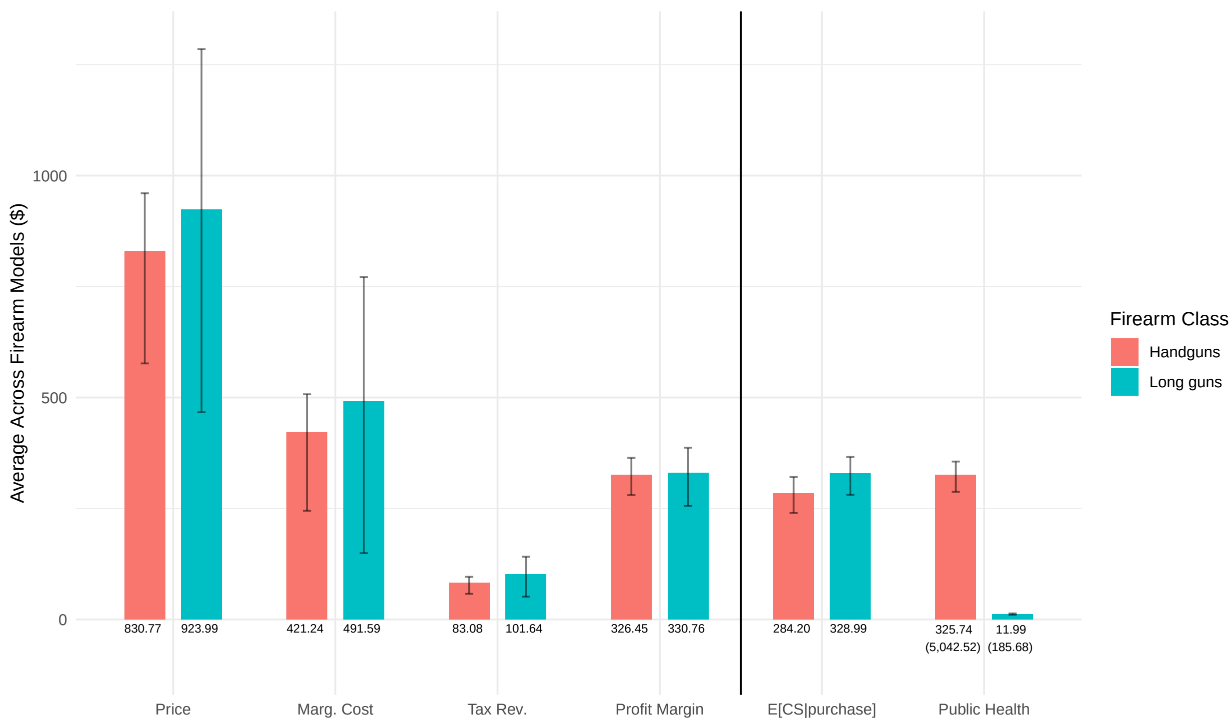
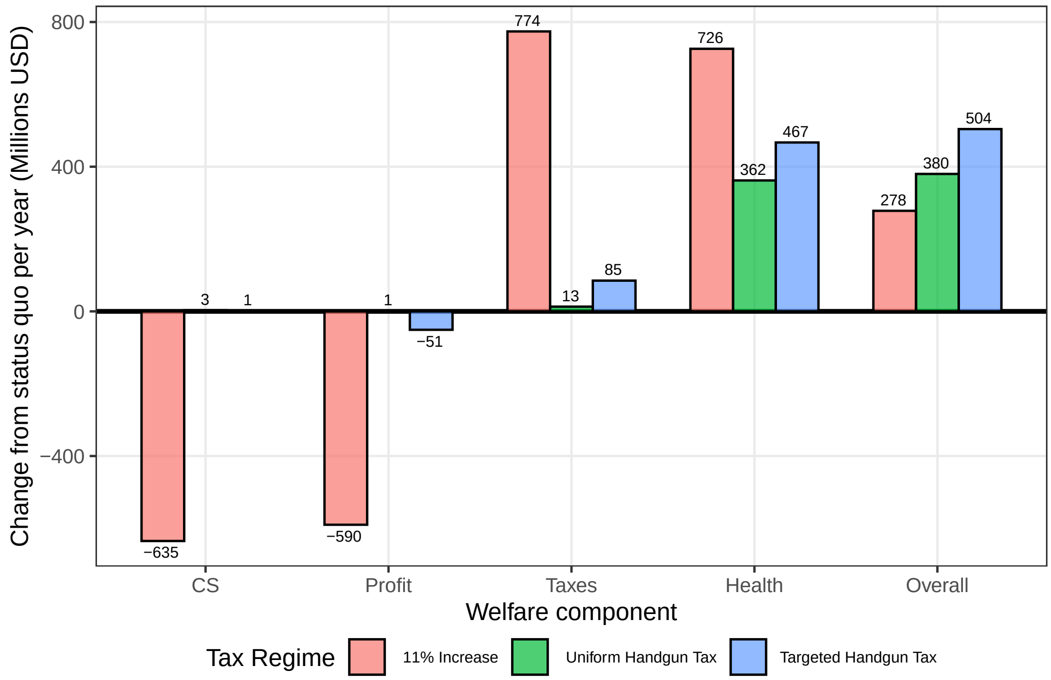
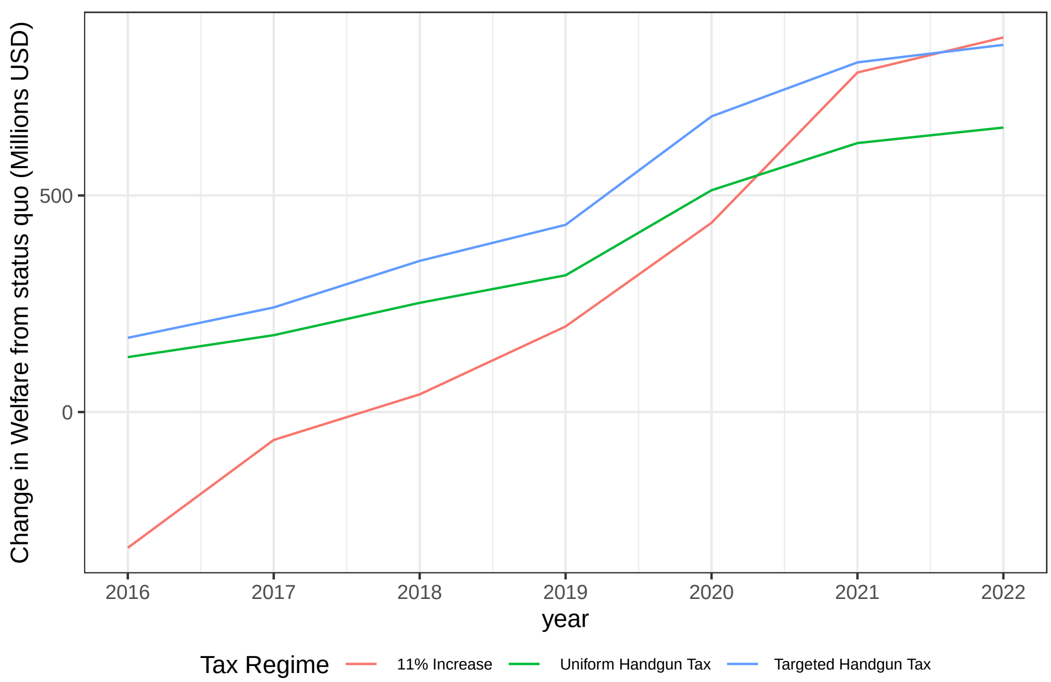


Figure 3: Distribution of Surplus from Firearm Purchase

Figure displays distribution of surplus from an additional firearm purchase, by firearm class. Bars are the unweighted-average of a statistic across firearm-years within a class. Bands are the unweighted 25th and 75th percentiles of the statistics. Price is the firearm's MSRP. Tax Revenue is the revenue to the federal government generated by the firearm's sale under status quo regulation $v_j p_{jt}$. Marginal cost is our estimate of the marginal production cost c_{jt}. Profit margin is our estimate of price, less taxes and marginal cost $p_{jt}(1 - v_j) - c_{jt}$. By construction, the sum of tax revenue, marginal cost, and profit margin equals the price. Consumer surplus measures the average value across consumers of purchasing each firearm, conditional on that firearm being the best alternative in their choice set. Public health is equal to the dollar value of homicides expected to be generated by a firearm one year after its purchase (i.e., a taller bar represents more damage from homicides). The net present value of the expected lifetime public health cost of a firearm purchase is in parentheses.



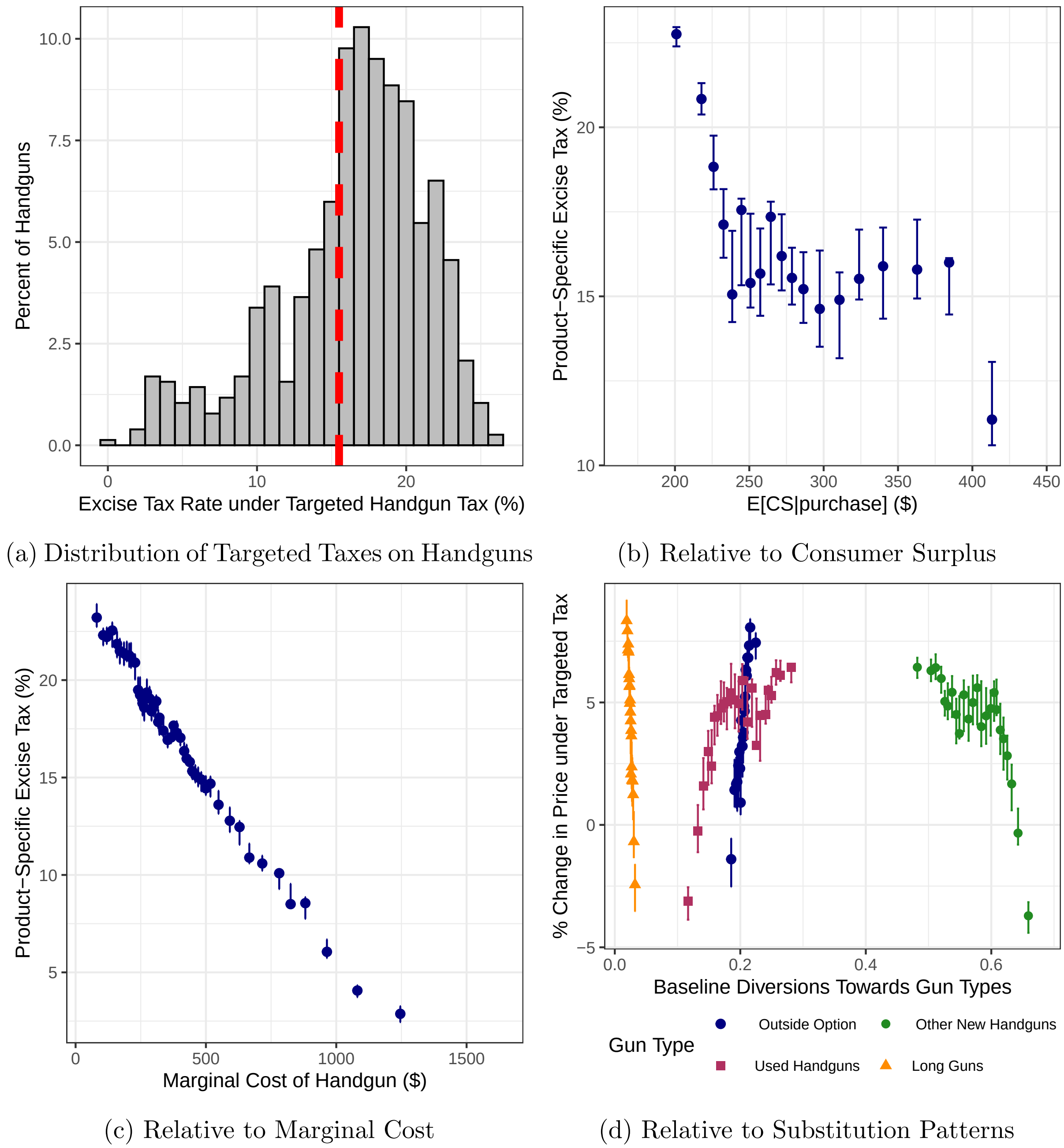
(a) Average Welfare Effects



(b) Overall Welfare Effects By Year

Figure 4: Equilibrium Welfare Effects of Firearms Tax Policies

Figure shows changes in welfare from the different tax policies we consider. In Panel (a), we show the average annual welfare effects of different tax policies in the U.S. during our sample, broken down by welfare components. In Panel (b), we show the overall welfare effects of different tax policies by year.



(a) Distribution of Targeted Taxes on Handguns

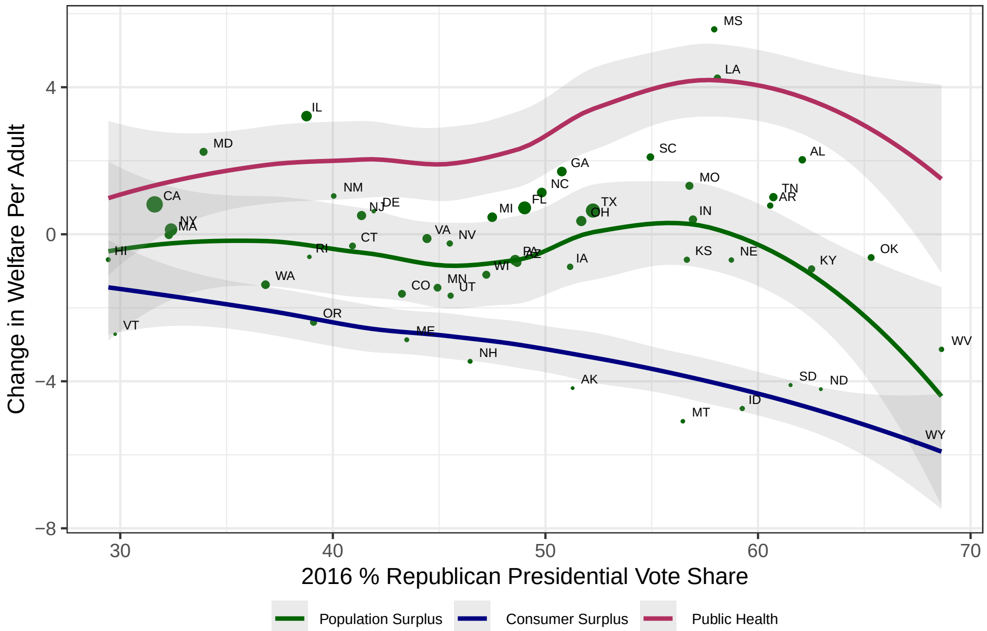
(b) Relative to Consumer Surplus

(c) Relative to Marginal Cost

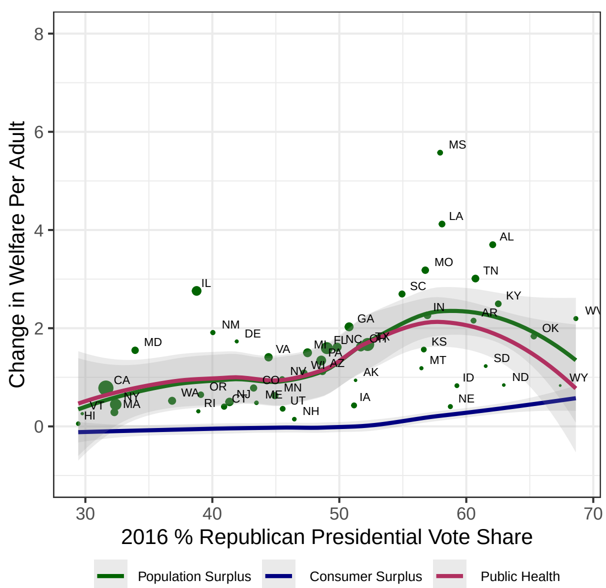
(d) Relative to Substitution Patterns

Figure 5: Incidence of the Targeted Handgun Tax Across Handgun Models

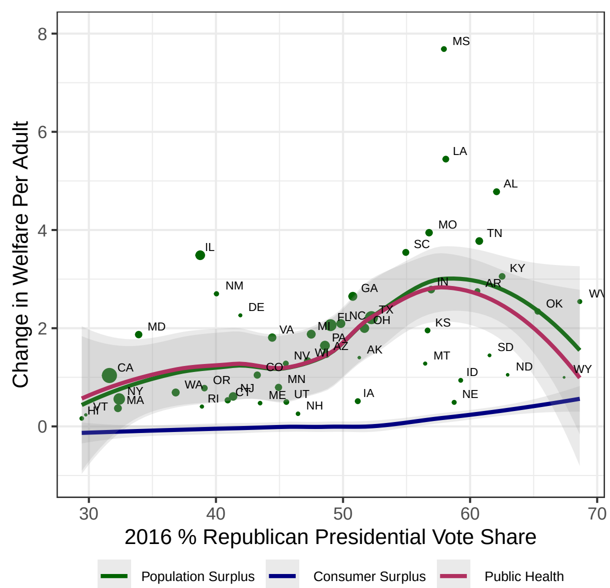
Panel (a) displays the distribution of the targeted handgun excise taxes, relative to the uniform handgun tax of 15.5% (dashed red line). Panel (b) displays a binscatter, with 95% confidence intervals, of the implemented handgun excise tax relative to the expected consumer surplus of buyers of each product in the current equilibrium. Panel (c) displays a binscatter, with 95% confidence intervals, of the implemented handgun excise tax as a function of each handgun model's marginal cost of production. Panel (d) displays a binscatter, with 95% confidence intervals, of the change in handgun prices from the current equilibrium, as a function of each handgun model's diversion ratio to a particular gun type. The number of bins is chosen using the data-driven procedure of Cattaneo et al. (2019), separately across panels.



(a) 11% increase in Excise Tax



(b) Uniform Handgun Tax



(c) Targeted Handgun Tax

Figure 6: Average Welfare Effects by Political Preferences

Figure shows changes in welfare components by U.S. State in equilibrium. Population Surplus is defined as the sum of consumer surplus, and the change in public health effects. The x-axis is the state-level % of votes for Donald Trump in the 2016 U.S. presidential election. The y-axis is the change in the welfare component from the tax policy, in 2022 dollars per adult. For each component, we plot a LOESS fit of the data, weighted by state population. The markers correspond to population surplus estimates and their size is proportional to the population of the state. Panel (a) plot the effects of a 11% increase in the excise tax on firearms. Panel (b) plots the effects of a 15.5% handgun excise tax coupled with no tax on long guns. Panel (c) plots the effects of the approximation to the optimal tax derived in Proposition 1.

OA.1 Optimal Excise Tax Derivation

This section derives the optimal excise tax formula presented in the main text, along with details on its implementation.

OA.1.1 Proofs

Proof of Proposition 1. In this proof, we suppress the index t and interpret each product j as a separate product × market. Let $\Phi(\vec{q})$ denote the negative externality from consumption, which is a function of all products purchased $\vec{q}$, and let $\phi_j \equiv \partial\Phi/\partial q_j$. Let τ_j denote the specific tax on product j. Since the proof concerns specific taxes, government revenue is defined as $\mathcal{G} = \sum_j \tau_j q_j$. Note that regardless of whether the tax is specific or ad valorem taxes, the sum of firm profits and government revenue is $\sum_j \Pi_j + \sum_j \mathcal{G} = \sum_j p_j q_j - C_j(q_j)$, where C_j is the cost function for producing j. Let $\omega_j = dC_j/dq_j$ denote the marginal cost of production for product j. A useful derivative to establish before proceeding is the effect of the tax on consumer surplus:

$$\begin{aligned} &\frac{\partial CS}{\partial p_j} = -q_j \\ \implies &\frac{\partial CS}{\partial \tau_k} = \sum_j \frac{\partial CS}{\partial p_j}\frac{\partial p_j}{\partial \tau_k} = \sum_j -q_j \frac{\partial p_j}{\partial \tau_k} \end{aligned}$$

The social planner solves:

$$\begin{aligned} \max_{\vec{\tau}} \quad & CS(\vec{p}) + \sum_j \Pi_j(\vec{p},\vec{q}) + \sum_j \mathcal{G}(\vec{p},\vec{q}) - \Phi(\vec{q}) \\ \text{subject to:} \quad & CS(\vec{p}) \geq CS_0 \end{aligned}$$

Letting λ denote the lagrange multiplier on the consumer surplus constraint, the problem can be recast as:

$$\max_{\vec{\tau}} \quad CS(\vec{p}) + \sum_j \Pi_j(\vec{p},\vec{q}) + \sum_j \mathcal{G}(\vec{p},\vec{q}) - \Phi(\vec{q}) + \lambda(CS(\vec{p}) - CS_0)$$

Or more compactly:

$$\max_{\vec{\tau}} \quad (1+\lambda)CS(\vec{p}) + \sum_j \Pi_j(\vec{p},\vec{q}) + \sum_j \mathcal{G}(\vec{p},\vec{q}) - \Phi(\vec{q})$$

Taking the first order condition with respect to τ_k, we have:

$$
\begin{aligned}
0 &= \frac{\partial}{\partial \tau_k}\Big((1+\lambda)CS(\vec{p}) + \sum_j \Pi_j(\vec{p},\vec{q}) + \sum_j \mathcal{G}(\vec{p},\vec{q}) - \Phi(\vec{q})\Big)\\
0 &= (1+\lambda)\sum_j -q_j\frac{\partial p_j}{\partial \tau_k} + \frac{\partial}{\partial \tau_k}\Big(\sum_j \Pi_j(\vec{p},\vec{q}) + \sum_j \mathcal{G}(\vec{p},\vec{q})\Big) - \sum_j \phi_j \frac{\partial q_j}{\partial \tau_k}\\
0 &= (1+\lambda)\sum_j -q_j\frac{\partial p_j}{\partial \tau_k} + \sum_j((p_j-\omega_k)\frac{\partial q_j}{\partial \tau_k} + \frac{\partial p_j}{\tau_k}q_j) - \sum_j \phi_j \frac{\partial q_j}{\partial \tau_k}\\
0 &= -\lambda\sum_j q_j\frac{\partial p_j}{\partial \tau_k} + \sum_j \frac{\partial q_j}{\partial \tau_k}(p_j-\omega_j-\phi_j)
\end{aligned}
$$

Let D be the matrix of demand price derivatives (e.g. $D_{j,k} = \partial q_j/\partial p_k$), and P be the passthrough matrix (e.g. $P_{j,k} = \partial p_j/\partial t_k$). Note now that $S = D \cdot P$, where $S_{j,k} = dq_j/dt_k$ is the total effect of tax on quantity (e.g. $dq_j/dt_k = \sum_m \partial q_j/\partial p_m \cdot \partial p_m/\partial t_k$). Stacking the first order conditions for each τ_k, We can express the above first order condition in matrix form as:

$$
\begin{aligned}
\vec{0} &= -\lambda P' \cdot \vec{q} + S'(\vec{p}-\vec{\omega}-\vec{\phi})\\
\implies \lambda P' \cdot \vec{q} &= S'(\vec{p}-\vec{\omega}-\vec{\phi})\\
\implies \lambda S'^{-1} P' \cdot \vec{q} &= \vec{p}-\vec{\omega}-\vec{\phi}
\end{aligned}
$$

Note that $S'^{-1} = D'^{-1}P'^{-1}$, so we can rewrite this as:

$$
\begin{aligned}
\lambda D'^{-1}P'^{-1}P' \cdot \vec{q} &= \vec{p}-\vec{\omega}-\vec{\phi}\\
\implies \lambda D'^{-1} \cdot \vec{q} &= \vec{p}-\vec{\omega}-\vec{\phi}
\end{aligned}
$$

For the right-hand side, we can rewrite $p_j = \omega_j + t_j + \mu_j$, where μ_j is the (post-tax) margin of product j, so that $\vec{p}-\vec{\omega}-\vec{\phi} = \vec{\tau} + \vec{\mu} - \vec{\phi}$. To simplify the left hand side, we use our assumption of Nash-Bertrand competition. In the general case, firm f solve the following problem:

$$
\max_{\vec{p}_f} \sum_{j \in f} (p_j - t_j)q_j - C_j(q_j)
$$

Taking a first order condition with respect to p_k, we have:

$$
\begin{aligned}
0 &= \frac{\partial}{\partial p_k}\Big(\sum_{j\in f}(p_j - t_j)q_j - C_j(q_j)\Big) \\
\implies 0 &= q_k + \sum_{j\in f}(p_j - t_j - \omega_j)\frac{\partial q_j}{\partial p_k}
\end{aligned}
$$

Which yields the familiar first order condition in matrix form:

$$
\begin{aligned}
\vec{0} &= \vec{q} + (\Omega \odot D)'(\vec{p} - \vec{c} - \vec{t}) \\
\implies \vec{\mu} &= -(\Omega \odot D)'^{-1}\vec{q}
\end{aligned}
$$

Where Ω is the ownership matrix of zeros and ones denoting which products j are owned by firms f, and $\odot$ denotes the Kronecker element-wise product. If we assume Ω is a matrix of ones, i.e. all products are owned by a single firm, its clear that $D'^{-1} \cdot \vec{q}$ is actually equal to the markups under a case of full monopoly/collusion in the market; call this $\vec{\mu}^M = -D'^{-1} \cdot \vec{q}$. Therefore, the optimal tax formula simplifies to:

$$
\begin{aligned}
-\lambda\vec{\mu}^M &= \vec{\tau} + \vec{\mu} - \vec{\phi} \\
\implies \vec{\tau} &= \vec{\phi} - \vec{\mu} - \lambda\vec{\mu}^M
\end{aligned}
$$

Or, for each element/product j

$$
\tau_j^* = \phi_j - \mu_j - \lambda\mu_j^M
$$

Which concludes the proof. □

In our empirical setting, ad valorem excise taxes are used instead of specific taxes. While our approximation to the optimal tax is based on the specific tax for simplicity, we show the proof for ad valorem excise taxes for completeness, and it is quite similar.

Proposition 2. *Suppose that firms firms engage in Nash-Bertrand price competition, and the social planner optimizes welfare as defined in Equation 1, choosing ad valorem excise taxes $v_{j,t}$, and is subject to a consumer surplus constraint as in Equation 2. Then the optimal ad* *valorem excise tax on product j in market t is:*

$$v_j^* = \frac{\phi_{j,t} - \mu_{j,t} - \lambda \cdot \mu_{0,j,t}^M}{p_{j,t}} \tag{OA.1}$$

Where $\phi_{j,t}$ is the magnitude of the (negative) marginal externality from consuming the product, $\mu_{j,t}$ is the margin charged by suppliers on their products, $\mu_{0,j,t}^M$ is the margin that would be charged under a monopoly or cartel conduct with no taxes, $p_{j,t}$ is the price of product j in market t, and λ is the shadow price (in welfare units) of the consumer surplus constraint.

Proof. As in the prior proof, we suppress the index t and interpret each product j as a separate product $\times$ market. Because the tax components in government revenue and firm profits cancel out under both specific and ad valorem taxes, the proof is identical up until the equation

$$\lambda D'^{-1} \cdot \vec{q} = \vec{p} - \vec{\omega} - \vec{\phi}$$

In the case of ad valorem taxes, we can rewrite $\vec{p} = \vec{p} \odot \vec{v} + \vec{\omega} + \vec{\mu}$, where $\vec{v}$ is vector of ad valorem tax rates, so that the right-hand side of the above equation is $\vec{p} \odot \vec{v} + \vec{\mu} - \vec{\phi}$. For the left-hand side, from the first order conditions in Equation OA.12, we derive that the markup is:

$$\begin{aligned}
0 &= (1 - v_k)q_k + \sum_{j \in f}((1 - v_j)p_j - \omega_j)\frac{\partial q_j}{\partial p_k} \\
\implies -(\vec{1} - \vec{v}) \odot \vec{q} &= (\Omega \odot D')(\vec{p} \odot (\vec{1} - \vec{v}) - \vec{\omega}) \\
\implies \vec{\mu} &= -(\Omega \odot D')^{-1}((\vec{1} - \vec{v}) \odot \vec{q})
\end{aligned}$$

Under monopoly, $\Omega \odot D' = D'$, so we have:

$$\vec{\mu}^M = -D'^{-1}((\vec{1} - \vec{v}) \odot \vec{q})$$

Because the Kronecker product does not commute (unless D is diagonal), we cannot further simplify our first equation. Instead, define $\vec{\mu}_0^M$ as the monopoly markup under zero ad valorem excise taxes ($\vec{v} = \vec{0}$). This reduces to $\vec{\mu}_0^M = -D'^{-1}(\vec{q})$ as before in the case of specific taxes. Using this as our estimate of monopoly markups, we can now rewrite the first equation of the proof as:

$$\begin{aligned}
-\lambda \vec{\mu}_0^M &= p \odot \vec{v} + \vec{\mu} - \vec{\phi} \\
\implies p \odot \vec{v} &= \vec{\phi} - \vec{\mu} - \lambda \vec{\mu}_0^M
\end{aligned}$$

Or, for each element/product j:

$$
\begin{aligned}
p_j \cdot v_j &= \phi_j - \mu_j - \lambda \mu_{0,j}^M \\
\implies v_j^* &= \frac{\phi_j - \mu_j - \lambda \mu_{0,j}^M}{p_j}
\end{aligned}
$$

□

Finally, we also implement the optimal tax in our assumption of competitive pricing, where $p_{j,t}(1 - v_{j,t}) = c_{j,t}$

The following proposition presents the optimal specific excise tax formula under the assumption that producers of new firearms provide their products at cost. The optimal tax under ad valorem taxes is once again very similar, only requiring division by $p_{j,t}$ as a modification.

Proposition 3. *Suppose that firms provide firearms at cost, and the social planner optimizes welfare as the sum of consumer surplus CS, government revenue $\mathcal{G}$, and negative externalities associated with consumption Φ, choosing specific excise taxes τ_j, and is subject to a consumer surplus constraint as in Equation 2. Then the optimal ad valorem excise tax on product j is:*

$$
\tau_j^* = \phi_j - \lambda \cdot \mu_j^M \tag{OA.2}
$$

Where ϕ_j is the magnitude of the (negative) marginal externality from consuming the product, μ_j^M is the margin that would be charged under a monopoly or cartel conduct with Nash-Bertrand competition, and λ is the shadow price (in welfare units) of the consumer surplus constraint.

Proof. The proof proceeds similarly to the prior two, but ignores the profit term in the welfare function. Note that under this tax and conduct assumption, we have that $\partial p_j / \partial \tau_j = 1$. The passthrough is zero from all other products' taxes. Since profits are no longer a part of welfare, government revenue and the tax component of profits no longer cancel out. Therefore, we need to derive the effect of taxes on government revenue:

$$
\begin{aligned}
\mathcal{G} &= \sum_j \tau_j q_j \\
\frac{\partial \mathcal{G}}{\partial \tau_k} &= q_k + \sum_j \tau_j \sum_m \frac{\partial q_j}{\partial p_m} \frac{\partial p_m}{\partial \tau_k} = q_k + \tau_k \sum_j \frac{\partial q_j}{\partial p_k} \\
\frac{\partial CS}{\partial \tau_k} &= \sum_j -q_j \frac{\partial p_j}{\partial \tau_k} = -q_k
\end{aligned}
$$

Letting Φ denote the negative externality from consumption as before:

$$\frac{\partial \Phi}{\partial t_k} = \sum_j \frac{\partial \Phi}{\partial q_j}\frac{\partial q_j}{\partial t_k} = \sum_j \phi_j \sum_m \frac{\partial q_j}{\partial p_m}\frac{\partial p_m}{\partial v_k} = \sum_j \phi_j \frac{\partial q_j}{\partial p_k}$$

Taking the full FOC with respect to welfare:

$$\begin{aligned}
\frac{\partial \mathcal{W}}{\partial \tau_k} &= (1+\lambda)\frac{\partial CS}{\partial \tau_k} + \frac{\partial \mathcal{G}}{\partial \tau_k} - \frac{\partial \Phi}{\partial \tau_k} = 0 \\
&= (1+\lambda) q_k + q_k + \sum_j (\tau_j p_j - \psi_j)\frac{\partial q_j}{\partial p_k} \\
\implies 0 &= -\lambda q_k + \sum_j (\tau_j p_j - \psi_j)\frac{\partial q_j}{\partial p_k}
\end{aligned}$$

Stacking the first order conditions and expressing in matrix form and proceeding as before yields the final formula:

$$\begin{aligned}
\vec{0} &= -\lambda \vec{q} + D'(\vec{\tau} - \vec{\phi}) \\
\vec{\tau} &= \psi + \lambda D'^{-1}\vec{q} \\
\vec{\tau}^* &= \vec{\phi} - \lambda \vec{\mu}^M \\
\tau_j^* &= \phi_j - \lambda \mu_j^M
\end{aligned}$$

□

OA.2 Details on Setting and Data

OA.2.1 Details on market size and consumer demographics

From the 2019 5-year American Community Survey (ACS), we record the count of each zip code's population and its distribution by gender, age, education, race/ethnicity, citizenship, poverty, health insurance status, and marital status in the zip code.[41]

To measure zip code voting behavior, we download the precinct-level vote shares in the 2016 U.S. presidential election, from Voting and Election Science Team (2018).[42] We aggregate precinct-level vote shares for all conservative candidates in the presidential election in 2016 to construct a "Percent Conservative" measure for each precinct in the United

[41]Downloaded from the IPUMS NHGIS page: https://www.nhgis.org/

[42]Downloaded from https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/NH5S2I

States.[43] We then aggregate this to the zip-code level using the supplied VEST precinct shapefiles along with U.S. Census TIGER ZCTA shapefiles, weighting precincts by total number of votes.

We employ to measures of consumer engagement with the NRA. We collect data from the Federal Election Commission on large ($200+) individual contributions to the NRA's Political Action Committee from 2016-2022, tagged with the donors zip code.[44] We map donations from the zip code to the congressional district using the December 2018 crosswalk from the U.S. Department of Housing and Urban Development.[45] As a complement, we use a dataset of grades issued to members of the U.S. House representatives in 2018 by the NRA, reflecting their political stances on gun rights legislation.[46]

Our survey data on participation in the firearm market comes from Wave 26 of the American Trends Panel (ATP), conducted by Pew Research in April 2017. We define an individual's participation in the legal firearm market as a binary indicator equal to 1 if the respondent stated that they (i) "personally own any guns (NOT including air guns, such as paintball, BB or pellet guns)," or (ii) "could see myself owning a gun." We also used this survey to gather information on respondents' demographic and political characteristics, taking care to match these variables as closely as possible to the data definitions from the ACS and election returns.

We construct our summary of participation in the firearms market via lasso-penalized linear regression on the survey data (Tibshirani 1996). Explicitly, and separately for each census region, we run a lasso regression of our indicator for potential market participation on the full set of Pew-provided characteristics for gender, age category, education level, race/ethnicity, citizenship, marital status, income category, health insurance, and party affiliation. We use an adaptive lasso procedure to then separately select the variables to include in each census region's linear probability model. Figure OA.1 shows the coefficients from each census region's selected model.

We construct measures of adults in the firearm market by zip code-gender cells. To construct the share of adults in the market within each cell, we take the inner product between the vector of selected regression coefficients the conformable vector describing the

[43]This includes Donald Trump of the Republican Party, Gary Johnson of the Libertarian Party, Evan McMullin (Independent) and Darrell Castle of the Constitution Party

[44]Source: https://www.fec.gov/data/browse-data/?tab=bulk-data. We filter for donations to both the regular NRA PAC and the Political Victory fund, the NRA's Super PAC.

[45]Source: https://www.huduser.gov/portal/datasets/usps_crosswalk.html.

[46]Source: https://www.thetrace.org/2018/10/nra-grades-republican-candidates/. These are derived primarily based on voting history and a questionnaire the NRA issues to candidates; an example questionnaire can be found here: https://afj.org/wp-content/uploads/2020/01/Wilson-Attachments-p450-453.pdf

cell's demographic and political characteristics. We compute the market size of each cell as the product of our estimated share with the cell's observed adult population size.

OA.2.2 Details on aggregate firearm purchase quantities

In this section, we describe adjustments made to publicly available NICS background check data to better reflect firearm purchases. For many firearm transactions since 1998, federal law requires the consumer first undergo a background check through the NICS system, called in by the firearm seller. To implement these background checks, the ATF administers a database that the party responsible for implementing the background check may query. The ATF makes counts of NICS queries to this database publicly available by state-month. These NICS counts have become a popular input for constructing measures of firearm purchases Lang (2016).

States differ in their NICS reporting on two important margins (Smucker et al. 2022). First, some states have permits that are exempt from reporting (known as "Brady Exempt"), meaning that holders of these permits may purchase firearms without a NICS check, for up to five years since the permit was issued. This could lead to an underestimate of firearms via NICS checks. For some permits, these exemptions only apply to handguns. Second, some state agencies act as a Point of Contact ("POC") between the firearm seller and the ATF. The POC is a state agency (e.g., the New Jersey Police Department) that takes responsibility for conducting background checks meeting both state and federal requirements. In implementing a background check for a single transaction, a state POC may query NICS multiple times. When this occurs, a measure of firearm purchases constructed from publicly available data on NICS queries may overstate the true number of firearm purchases that actually occur.[47] State agencies differ in whether all background checks are conducted through a POC, or those solely on handguns.

Figure OA.2 displays the status of all US states in their reporting standards to NICS in 2016.[48] We see that states in the South are more likely to have Brady exempt permits, suggesting that the NICS reporting may be biased downward in states with higher underlying demand for firearms.

Throughout, we rely on the standard adjustment to NICS checks from Brauer (2013), which adjusts background checks to account for multiple firearms purchased per background

[47] For example, suppose the New Jersey POC queried NICS two times for each firearm background check they were required to conduct. In this case, publicly available data on NICS checks would be two times higher than the true number of firearm purchases.

[48] Figure is copied from the 2016 NICS Operations report, downloaded from https://www.fbi.gov/file-repository/cjis/2016-nics-operations-report-final-5-3-2017.pdf/view

check. This formula is

$$NICS_{s,t} = 1.1 \cdot \text{HandgunChecks}_{s,t} + 1.1 \cdot \text{LongGunChecks}_{s,t} + 2 \cdot \text{MultipleFirearmChecks}_{s,t} \quad \text{(OA.3)}$$

We follow a three-step approach to adjust NICS background checks to better reflect firearm purchases. First in states where we observe physical transfers, we use these in lieu of NICS checks. Second, in states with POC checks, we estimate the relationship between NICS checks and POC checks to correct for multiple queries. We convert these to purchases using Equation OA.3. Third, in states with Brady exempt permits, we estimate a sythetic difference-in-difference model (Arkhangelsky et al. 2021) to adjust for under-reporting from Brady exemptions.

OA.2.2.1 Over reporting in POC states

To correct for over-reporting from POC states, we manually collect POC information from state agencies for all states with POCs during our sample, where data was publicly available. Table OA.1 displays the states with POCs and the data we were able to collect. For 11 of 17 states with a state POC, we are able to observe the state-level background checks to correct for multiple queries per transaction, and for 5 of these states, state agencies also report the number of transactions or transfers.

Figure OA.3 displays the relationship between State POC background checks and physical transfers, for state-years in which we were able to construct both variables. The relationship, whether we allow for state-specific slopes or not, is very close to 1. We take this as evidence that POC background checks are a suitable proxy for firearm purchases.

We adjust observed NICS purchases in POC states to account for the fact that the state POC may query NICS more than once per background checks. Specifically, we assume a constant adjustment factor $\text{StatePocChecks}_{s,t}/M_{s,t} = \alpha_s \cdot NICS_{s,t}/M_{s,t}$ to convert NICS data from POC states to physical firearm transfers, where $M_{s,t}$ denotes the market size. Each state has a different constant of proportionality α_s, which we estimate as state fixed effects via OLS, after taking logs of the assumed relationship.

Table OA.2 presents estimates of state-specific constants of proportionality α_s, along with an average estimator assuming no state heterogeneity. These state-specific constants have a low of 0.79 in Colorado, which implies each background check by the Colorado POC requires $1/0.79 \approx 1.27$ NICS checks. The high is 1.04 in Utah, which would be the case if some background checks from the Utah POC did not require a call to the NICS system. The average effect of $\alpha_{\text{average}} = 0.94$ implies that, for the average state-year, 100 POC checks requires $100/0.94 \approx 106$ NICS checks. We apply state-specific adjustment factors to POC states where available, and the average α_{average} to the remaining POC states. We then use the time series of adjusted NICS checks by state for the remaining correction for brady exemptions.

The output of our process is an estimate of the number of NICS checks that would have occurred in each POC state in OA.1, had they counterfactually not had their POC in place. These predictions are comparable to the number of NICS checks in state-years without a POC, and we refer to these comparable predictions as "NICS checks" in the following section.

OA.2.2.2 Under reporting in Brady exempt states

To correct for under-reporting from Brady exemptions, We use historical changes in Brady exempt status by state, and construct a synthetic difference-in-difference estimator Arkhangelsky et al. (2021) to estimate the effect of Brady exemptions on NICS background checks for each switching state. This approach uses 21 states (donors) with no brady-exempt permits from 2004-2023 to construct a counterfactual time series of NICS checks in the absence of the introduction of a brady-exempt permit. Where the synthetic difference-in-difference estimator differs from a standard synthetic control is it also allows for weights on time period to match pre-treatment trends. Explicitly, we assume the following data generating process for NICS checks per capita.

$$\log(\frac{NICS_{s,t}}{Pop_{s,t}}) = \vec{\theta}_s \cdot \upsilon_t + \gamma_s + \delta_t + \beta_s \cdot BradyExempt_{s,t} + \epsilon_{s,t} \tag{OA.4}$$

Which accommodates unobservable latent factors at both the time and state level. Table OA.3 displays each treated state that moves to obtaining a brady-exempt permit, along with the estimated effects of Brady exempt-status on total NICS checks (Equation OA.3), Handgun checks, and long gun checks. Brady Exemptions lead from anywhere from a .6% decrease (Oklahoma) to a 69% decrease (Alabama) in NICS checks. The average is a 30% decrease. We apply state-specific estimates for these 10 states for which we observe a change in brady exempt status in months with a valid brady exempt permit. For the other 13 states with brady exempt permits throughout our sample, we apply the average effect of a 30% decrease in NICS checks.

We perform a similar adjustment to three states with Handgun permit exemptions (known as "Partial Permit POC" states) during our sample. These states only exempt handgun purchases from NICS checks for those with valid permits and can demonstrate patterns of NICS records quite different from states with a simple Brady exemption. For these partial permit states, we use the transition from partial permit status to full reporting. Table OA.4 displays the estimated effects. Consistent with the exemption only applying to handguns, we estimate no effect on long gun checks, and a 180% *increase* in handgun gun checks from removing partial permit status. We apply these state-specific estimates to months with partial permit status in the two states during our sample with the exemption (Michigan and Iowa), and apply the average effect of a 180% increase in handgun checks to North Carolina and Nebraska, for which we observe no change in exemption.

Figure OA.5 displays the final ratio of the adjusted NICS checks to unadjusted NICS checks from 2016-2022, by state. On average, our adjustments increase purchases by 30% nationally. Southern states and states in the Mountain west have the largest adjustments, reflecting the prevalence of Brady exemptions in these regions.

Our adjusted measure of NICS background checks simultaneously accounts for POC status, Brady exemptions, and Partial Permit POC rules. We use our adjusted measure of NICS background checks to construct moments in Section 5.3, as we believe they are a more faithful estimate of firearm purchases by state-year.

OA.2.3 Matching of Blue Book and FRB Gun Models

In this section, we describe our matching procedure to merge models in the FRB to BBGV gun IDs. First, we manually match all makes, by unique (lowercase) string, with at least 30 transactions in our time period in Massachusetts to their corresponding manufacturer ID in BBGV. 95% of all transactions in FRB are matched to a BBGV manufacturer ID.

We then preprocess gun model names in both datasets. We remove non-alphanumeric characters, remove the standalone word "model", which we view as uninformative, and appears in many FRB and BBGV model names, convert roman numerals to numbers (e.g. $II \rightarrow 2$), and then tokenize the string so that words appear in alphabetical order, followed by any tokens that are numbers. This latter point is done to ensure that the model numbers, which are often the key identifiers of guns, occupy the same part of the string and therefore the matching algorithm weights these corresponding more closely. We then match processed gun names, in the FRB, to the most similarly named gun in BBGV. The candidate BBGV models are constrained to be within manufacturer and weapon class, as well as have price data (new or used) in the years we observe transactions in the FRB.[49] We use the weighted ratio score of the `fuzzywuzzy` Python package to match strings, and retain matches with at least a 60% similarity score. We choose this relatively low threshold to ensure as many matches as possible, and we do not ignore some transactions in our demand estimation simply due to a low quality string match; though this will introduce additional estimation error to our demand system. We proceed assuming the matched BBGV gun model is the true

[49]This latter condition is used to avoid matching FRB guns to BBGV models that were released after we observe transactions.

gun model represented in the FRB data. If there are ties, we break them by an indicator of whether the gun is in active production (has an MSRP for the year), followed by the number of years for which MSRP data is available. In total, through this procedure, we are able to match 90% of FRB transactions to a BBGV ID, for a total of 7,616 unique BBGV gun models. About 70% of transactions occur in years where the BBGV models are actively produced.

Finally, we complete the merge by assigning each transaction a common set of gun characteristics by BBGV model ID, taken as the median FRB value in the FRB, across transactions. As a validation of the merge, the imputed values agree with the recorded gun model characteristics: the imputation for high-capacity agrees 80% of the time, and the standard deviation of the imputation error for barrel length is 85% lower than the standard deviation of barrel length.

OA.3 Model Estimation Details

OA.3.1 Estimation Routine

We estimate the demand model in four steps. First, we estimate the mean utilities and parameters governing preference heterogeneity $\theta = (\delta_{j,t}, \rho, \alpha, \Pi, \Sigma, \Pi_\alpha, \sigma_\alpha, \Pi_\omega, \sigma_\omega)$ via constrained MLE ((Goolsbee and Petrin 2004), (Train 2009)) using the FRB transaction microdata in Massachusetts. Next, we estimate the baseline parameters governing tastes for characteristics β via a projection of δ_j on the time-invariant characteristics X_j. That is, we run the linear regression specified in Equation 7, then uses the estimated fixed effects $\hat{\delta}_j$ to estimate β via a GLS regression, weighted by the variance matrix of fixed effects $\hat{V}$ (Nevo 2000). Next, we estimate the market-specific tastes for firearms τ_t across state-years using the adjusted NICS background check data, which captures differences in aggregate tastes for firearms across state-year. Finally, we recover the marginal costs $c_{j,t}$ using the first order conditions of the supply side, given the estimated demand parameters.

We collapse the Massachusetts FRB data by gender-zip code-demographic cell, denoted d, each year y. Let $\mathcal{T}_{MA}$ denote the markets (state-years) in Massachusetts, $N_{j,d,t}$ the number of individuals purchasing product j in demographic cell d, and $\mathcal{D}_{MA}$ the set of these demographic cells. Conditional on d, consumers in each cell differ only due to the normally distributed unobserved heterogeneity, so demographic cell market shares are as follows:

$$Pr(j|d, s, t) = \int_{\vec{\nu}} Pr(j|D_i = d, t, \nu_i = \nu, s)\phi(\vec{\nu})d\vec{\nu} \tag{OA.5}$$

where ϕ represents the standard multivariate normal pdf. As this high-dimensional integral has no closed form, we approximate its value using sparse grid quadrature (Conlon and Gortmaker 2020). We solve the following constrained maximum likelihood problem:

$$\max_{\theta} \sum_{t} \sum_{d \in \mathcal{D}_{MA}} \sum_{j \in \mathcal{J}_t} N_{j,d,t} \log(Pr(j|d,s,t)) \tag{OA.6}$$

$$\text{Subject to: } Pr(j|t) = \hat{s}_{j,s,t} \quad \forall j \in \mathcal{J}_t, s = MA \tag{OA.7}$$

$$E[\xi_{j,t} \cdot \vec{Z}_{j,t}] = 0 \tag{OA.8}$$

$$E[\phi_{c,t} \cdot \tilde{J}_{c,t}] = 0 \quad \forall c. \tag{OA.9}$$

This is a standard MLE problem, with three sets of additional constraints which we explain below. Equation OA.7 constrains the predicted state-level choice probabilities $Pr(j|t)$ to match the empirically observed choice probabilities/market shares $\hat{s}_{j,t}$ in the FRB data (Goolsbee and Petrin 2004). Given θ, $Pr(j|t)$ can be calculated by integrating over the distribution of demographic cells d in Massachusetts.

$$s_{j,t} = Pr(j|t) = \frac{\sum_{d \in \mathcal{D}_{MA}} M_{d,t} Pr(j|d,t)}{\sum_{d \in \mathcal{D}_{MA}} M_{d,t}} \tag{OA.10}$$

where $M_{d,t}$ is the market size (potential gun consumers) belonging to demographic cells d. The empirical analogue to this model-derived probability is the quantity $\hat{s}_{j,t}$, the empirically observed probability of gun j being chosen in market t:

$$\hat{s}_{j,t} = \frac{\sum_{d \in \mathcal{D}_{MA}} N_{j,d,t}}{\sum_{d \in \mathcal{D}_{MA}} M_{d,t}}$$

This constraint exactly identifies the mean utilities $\delta_{j,t}$ across products. We implement this constraint via the contraction mapping suggested in Conlon and Gortmaker (2020).

A threat to identification of θ, and in particular α, is that the national MSRP $p_{j,t}$ may be correlated with the unobserved product-year demand shock $\xi_{c,t}$, due to market power among firearm manufacturers. For this reason, we also impose during optimization the moment in Equation OA.8, that the demand shock is orthogonal to a matrix of instruments. For identifying α, we use the same (residualized) manufacturer specific commodity response functions $Z_{1,j,t}$ described in Section 4.1[50]. This ensures that α is identified off of price shifts unrelated to demand shifts. It is analogous to the moments used in Berry et al. (1995) to

[50]Residuals are taken by regressing the instrument on product and class-year fixed effects. To increase the power of these instruments, we perform the LASSOIV procedure on all products seen in the BBGV data that share a manufacturer with a product in the demand model. Note also that the composite goods $\omega_{c,t}$ are excluded from this expectation.

identify price sensitivity in a method of moments demand estimation framework.

Identification of the nesting parameters ρ_1, ρ_0 requires instruments that shift the market shares of products conditional on class $Pr(j|i,t,j \in c)$, and weapon class shares conditional on purchase $Pr(j \in c|i,t,j \neq 0)$, respectively (Verboven 1996). To identify ρ_1, we include in $\vec{Z}_{j,t}$, a variant of the differentiation instruments proposed in Gandhi and Houde (2019), denoted $Z_{2,j,t}$, that measures the relative impact of cost shocks with respect to rival goods in the same nest:

$$Z_{2,j,t} = \sum_{k \in c(j), f(j) \neq f(k)} (Z_{1,j,t} - Z_{1,k,t})^2 \tag{OA.11}$$

This instrument captures the relative impact of cost shocks on demand for product j, relative to its competitors owned by different firms f that are in the same class, and should be negatively correlated with conditional product shares.

Our final constraint (Equation (OA.9)) uses variation in the choice set size to identify the outside option nesting parameter ρ_0. We implement this identification econometrically by satisfying that the time series of preference shocks ϕ_{cy} is orthogonal to time series variation in the (de-meaned) count of firearm models $\tilde{J}_{c,t} = |\mathcal{J}_{c,t}| - \frac{1}{N_{c,t}} \sum_{c,t} |\mathcal{J}_{c,t}|$ in each class. This moment condition extends the approach of identifying the nesting parameter based on the entry and exit of goods from the choice set to our setting with multiple levels of nesting (e.g., Miller and Weinberg 2017, Gandhi and Nevo 2021). Choice set size, ceterus paribus, should be positively correlated with conditional class shares.

To interpret the choice set variation that identifies the nesting parameter ρ_0, Panel (a) of Appendix Figure OA.13 shows the variation from year-to-year in the size of the choice set $|\mathcal{J}_{c,t}|$ over our sample. Much of the variation in the choice set size comes from eight mergers and acquisition activities occurring across the 58 manufacturers in our sample. For example, in Panel (b), we plot a case study of the change in the number of models produced (according to the Blue Book of Gun Values) by Remington and Marlin Firearms, two manufacturers owned by Remington Outdoor Company. In 2020, Remington Outdoor Company filed for bankruptcy, and the two manufacturers were sold to different companies (Sturm Ruger and Roundhill Group).[51] Collectively, these manufacturers accounted for approximately 5% market share of new guns sold in Massachusetts prior to the bankruptcy in 2019, dropping to less than 1% percent by 2021, in part because Roundhill group delayed production and eventually closed a major firearms plant.[52]

To identify the parameters governing heterogeneous tastes for gun characteristics $\Pi, \Pi_\alpha, \Pi_\omega$, we use the differential buying patterns within a product across consumers in different gender-

[51] Source: https://www.nytimes.com/2020/07/28/business/remington-bankruptcy-guns.html

[52] Source: https://www.wktv.com/news/top-stories/remarms-ilion-operation-to-close-march-2024/article_55edb272-8fbd-11ee-9b84-1b80825a8ee7.html

zip code cells. We identify the scale of the unobserved heterogeneity $\Sigma, \sigma_\alpha, \sigma_\omega$ via the entry and exit of products with differing characteristics.

Given our demand estimates, we recover the marginal costs of production for each firearm model using the firm's first order conditions for profit maximization. Given the profit objective in Equation 8, the first order condition for firm f's profit maximization is as follows:

$$\frac{\partial \Pi_f}{\partial p_j} = (1 - \upsilon_j) q_{j,t} + \sum_{k \in \mathcal{J}_f} (1 - \upsilon_k) p_{k,t} \frac{\partial q_{k,t}}{\partial p_j} - c_{k,t} \frac{\partial q_{k,t}}{\partial p_{j,t}} = 0 \tag{OA.12}$$

Re-arranging this first order condition, we obtain an expression for the marginal cost of firearms production:

$$\vec{c}_f = (1 - \vec{\upsilon}_f) \otimes (\vec{p}_f - \Delta_f^{-1} \cdot \vec{q}_f) \tag{OA.13}$$

where Δ_f is the $|\mathcal{J}_f| \times |\mathcal{J}_f|$ matrix of cross-price derivatives (e.g. $\Delta_{j,k} = \partial q_j / \partial p_k$). Given estimates of demand using the approach outlined in Section OA.3.1, we can recover the marginal cost directly from the firm's first-order condition.

OA.3.2 Model Validation

In this section, we provide details on out-of-sample moments we compare our model estimates to for validation. Figure OA.15, we assess the fit of our demand model, using out-of-sample moments from four distinct data sources. In Panel (a), we use additional information from NICS on the share of hand vs long gun background checks in each state, allowing us to compare the fraction of handgun purchases observed in each state against the fraction predicted by our model, conditional on any purchase.[53] This is an out of sample test, since the vertical taste-shifter $\tau_{s,t}$ is estimated from only transaction data in Massachusetts and total NICS checks in other states, not broken down by firearm class. Therefore, variation in the predicted share of handgun purchases is driven solely by the demographic differences across state. This captures the extent to which our estimates of demographic preferences from Massachusetts can explain handgun purchase rates in other states. Our model is unable to exactly fit the data, over-predicting the share of handgun purchases in most states. This may be due to differences in laws concerning handgun purchases across states, which are not accounted for in our model. At the same time, the model predicts patterns in the right direction: the correlation between our predicted handgun purchase rate and the observed handgun background check rate is 0.40., and apart from Hawaii, there are no notable outliers.

In Panel (b), we compare the predicted total quantity of new gun purchases attributable

[53] We exclude Nebraska, Iowa, and North Carolina from the figure, as these states are partial permit states that do not require background checks for handguns if the purchaser has a permit.

to each firm in our model, to the total number of new guns manufactured by each firm in 2016, according the ATF. Like the background check data, we would not expect a one-to-one relationship between guns sold and guns produced, since it may take time for guns to travel from the manufacturer to the end user. Nonetheless, we estimate a strong correlation between our model's predictions and the data: the correlation in the log quantities of the model predictions for each firm and the ATF data is 0.69. Importantly, there does not appear to be a systemic under or over prediction of the number of guns produced by each firm.

In Panel (c), we plot the the implied excise tax revenue over time for newly produced guns $\sum_{j\in\mathcal{J}_\dagger} p_j q_j v_j$ from our structural model, along with the actual excise tax revenue collected by the U.S. government by quarter.[54] We observe very similar trends, the levels of revenue from our model are somewhat higher (640M$ in FAET, vs 730M$ implied annually by our model), particularly in the earlier part of the sample.

Since we rely on cross-neighborhood heterogeneity in demographics from Massachusetts to identify demographic preferences β_i, α_i, our extrapolation relies on this heterogeneity across zip codes in Massachusetts to reflect national patterns. Since Massachusetts is one of the most left-leaning states, we worry estimates of preferences along political dimensions may not be reflective of the broader United States. To test this, we compare in Panel (d) estimates of τ, the state-year taste shifter, to the % in each state voting conservative in the 2016 presidential election, to validate our estimates of demographic heterogeneity. Recall τ is the residual preference for firearms after accounting for demographics. If purchasing patterns in conservative neighborhoods in Massachusetts are informative about national patterns, we would expect that this shock is uncorrelated with the political leaning of the state. We find that there is very little correlation between τ and conservative voting patterns in the state, suggesting our demographic preferences in Massachusetts along this dimension are representative of the greater United States population.

This suggests our model is able to accurately capture national patterns in firearm demand, despite using only data on aggregate quantities in states other than Massachusetts.

[54]Data collected from https://www.ttb.gov/system/files?file=images/foia/xls/Quarterly-breakdown-of-FAET-collections.xlsx. Note that we lag FAET revenue by one quarter to reflect the revenue for corresponding sales.

OA.4 Details on Model of the Firearm Stock and Homicides

OA.4.1 Initial Conditions

Our calibration of the initial firearm stock utilizes the following decomposition:

$$Q_{c,s,2015} = \text{HH}_{s,2015} \times \frac{\text{Adults with gun in HH}_{s,2015}}{\text{Adults}_{s,2015}} \times \frac{\text{Gun owners}_{2015}}{\text{HH with gun}_{2015}} \times \frac{\text{Guns}_{c,s,2015}}{\text{Gun Owner}_{s,2015}}.$$

There are direct measurements of the first two terms—the number of households per state and the share of adults living in a household with a firearm—in publications from the ACS and Schell et al. (2020), respectively.

We measure the final two terms using microdata from the 2015 National Firearm Survey (Azrael et al. 2017). To calculate the number of firearm owners per household with at least one firearm, we compute the average number of firearm owners per household, as reported by survey respondents who personally owned a firearm. We use these same respondents to compute the average count of class c firearms per owner.[55]

OA.4.2 Calculating the handgun-share of firearm homicides

Our calculation of the handgun share of firearm homicides excludes incidents in which the firearm class was not known and assumes that such data are missing at random. Our preferred calculation takes observations of the share of firearm homicides in which a handgun was used by state-year from the National Violent Death Reporting System, and aggregates across state years using weights based on the count of homicides in the CDC vital statistics. We calculate analogous ratios using the FBI's Supplemental Homicide Records and using three different weighting schemes for each average: equal weighting by state-year, weights proportional to firearm homicides in which the firearm class is known, or weights proportional to total firearm homicides. Across these six different measurement approaches, the calibration target ranged from 88.9–90.8. The firearm class is observed in approximately 56 percent of firearm homicides in the NVDRS records and 48 percent of firearm homicides in the SHR records, with low correlation in missingness across the two data sources.

[55] We average across firearm owners by Census region—not by state—to avoid survey noise in strata with few observations. In practice, the average guns of each class per owner do not vary much by region, so this assumption is relatively unimportant.

OA.4.3 Inference

We perform inference on our estimates of the degradation rate $\hat{\varphi}$ and the class-specific elasticities of homicides with respect to the firearm stock $\hat{\kappa}_c$.

We perform inference for the degradation rate $\hat{\varphi}$ by adjusting for sampling uncertainty in the surveys of adults used to construct the measures of the firearm stock in 1994 and 2015. We accessed the underlying survey data from Cook and Ludwig (1996) and Azrael et al. (2017), from which we compute standard errors for their reported estimates of Q_{1994} and Q_{2015}, respectively. We then bootstrap our procedure for calibrating the degradation rate $\hat{\varphi}$ across bootstrap replicates. Q^b_{1994} and Q^b_{2015}. In forming the replicates, we draw from a bivariate normal distribution, with means equal to the published estimates of the stock, standard deviations equal to our estimated standard errors of the stock, and correlation zero. We do not account for sampling uncertainty in the flow of new firearms q_t, as these quantities are measured without sampling uncertainty in administrative data. We form a standard error for $\hat{\varphi}$ as the standard deviation of our estimates across bootstrap replicates.

We perform inference on our estimates of the class-specific elasticities of homicides with respect to the firearm stock $\hat{\kappa}_c$ by averaging the state-year derivatives of the calibration objective with respect to the model parameters, adjusting for the inverse of their (non-diagonal) estimated variance-covariance matrix. We do not adjust for uncertainty in $\hat{\varphi}$, nor in the the published estimates of the aggregate elasticity of homicide with respect to the firearm stock.

OA.5 Details on Counterfactuals

This section provides details on our analysis of counterfactual firearm regulations in Section 7.

OA.5.1 Welfare components

This section formalizes the components appearing in our measure of welfare as a function of a counterfactual tax change $\Delta\vec{v}$.

Implementing the counterfactual tax change $\Delta\vec{v}$ leads to a counterfactual tax rate $(\vec{v} + \Delta\vec{v})$. Firms re-optimize under the counterfactual tax rate, setting yearly prices $\vec{p}_t(\Delta\vec{v})$. Consumers re-optimize their purchases—facing the new prices $\vec{p}(\Delta\vec{v})$—giving rise to counterfactual yearly quantities $\vec{q}_t(\Delta\vec{v})$.

Industry profits in year t are

$$\Pi_t(\Delta\vec{v}) = \sum_f \Pi_{f,t}(\Delta\vec{v}) = \sum_{j\in\mathcal{J}_{f,t}} (1 - v_j - \Delta v_j) \times p_{j,t}(\Delta\vec{v}) \times q_{j,t}(\Delta\vec{v}) - c_{j,t} \times q_{j,t}(\Delta\vec{v}), \quad \text{(OA.14)}$$

where the summation is across profits from each firm f during year t. The in-sample change in profits is

$$\Delta\Pi(\Delta\vec{v}) = \sum_{t=2016}^{2022} \Pi_t(\Delta\vec{v}) - \Pi_t(\vec{0}). \quad \text{(OA.15)}$$

Consumer surplus in state s during year t is calculate in its typical form, as expected utility divided by the price coefficient:

$$CS_{s,t}(\Delta\vec{v}) = M_s \int_{i\in s} \frac{1}{\alpha_i} E_i \left[\max_{j\in\mathcal{J}_t\cup\{\omega_h,\omega_l\}\cup\{0\}} u_{i,j,s,t}(\vec{p}_t(\Delta\vec{v})) \right] \partial F_s(i), \quad \text{(OA.16)}$$

where the utilities depend on the tax change $(\Delta\vec{v})$ indirectly through the prices $\vec{p}(\Delta\vec{v})$. The integral is taken across the joint distribution of observed and unobservably heterogeneous consumers in state s. The inner expectation can be computed under the assumed nested logit distribution on the *iid* shocks $\epsilon_{i,j,s,t}$. The in-sample change in consumer surplus is

$$\Delta CS(\Delta\vec{v}) = \sum_{t=2016}^{2022} \sum_s CS_{s,t}(\Delta\vec{v}) - CS_{s,t}(\vec{0}). \quad \text{(OA.17)}$$

We also use the value

$$CS_0 = \sum_{t=2016}^{2022} \sum_s CS_{s,t}(\vec{0}) \quad \text{(OA.18)}$$

to calculate the consumer surplus constraint for the constrained optimal tax.

Tax revenue to the federal government from the sales of firearms from manufacturers in year t is

$$G_t(\Delta\vec{v}) = \sum_j (v_j + \Delta v_j) \times p_{j,t}(\Delta\vec{v}) \times q_{j,t}(\Delta\vec{v}) \quad \text{(OA.19)}$$

The in-sample change in government revenue is

$$\Delta G(\Delta\vec{v}) = \sum_{t=2016}^{2022} G_t(\Delta\vec{v}) - F_t(\vec{0}). \quad \text{(OA.20)}$$

We do not consider other forms of revenue, such as state and local sales taxes, corporate taxes, or income taxes on the workers who manufacture firearms.

The in-sample change in homicides in state s and year t is

$$\Delta d_{s,t}(\Delta\vec{v}) = \sum_c d_{c,s,t}\left(\left(\frac{(1-\varphi)^{t-2015}Q_{c,s,2015} + \sum_{t'=2016}^{t}(1-\varphi)^{t-t'}q_{c,s,t}(\Delta\vec{v})}{(1-\varphi)^{t-2015}Q_{c,s,2015} + \sum_{t'=2016}^{t}(1-\varphi)^{t-t'}q_{c,s,t}(\vec{0})}\right)^{\kappa_c} - 1\right), \tag{OA.21}$$

which accumulates over time. The overall in-sample change in homicides is

$$\Delta d(\Delta\vec{v}) = \sum_s \sum_{t=2016}^{2022} \Delta d_{s,t}(\Delta\vec{v}). \tag{OA.22}$$

OA.5.2 Optimal Tax Implementation

To implement an estimable version of the optimal excise tax presented in Proposition 1, denoted the "Targeted Handgun Tax" in our counterfactuals, we require estimates of the marginal externality ϕ_j, the margin μ_j, the monopoly margin μ_j^M, and the shadow price of the consumer surplus constraint λ. Each of these are equilibrium objects, which will depend on the actual tax levels set. Rather than solve a complex iteration of tax schemes until a fixed point is found, we opt instead for a "sufficient statistics" approach as in Allcott et al. (2019) and use estimates from other counterfactual simulations. As described in the main text, since the margin on long guns ranges from \$300-\$500, while the net present value of their externality is \$185, we set excise taxes on all new long guns to zero. We describe our approach to estimating each of the relevant components to taxes on handguns below.

- $\hat{\mu}_j$: We use as estimates the equilibrium profit margin and price from our counterfactual estimates of a uniform handgun only tax.

- $\hat{\mu}_j^M$: To estimate this, we use the margins from the counterfactual exercise of monopoly ownership of firearms under the baseline excise taxes of 10%-11%, whose welfare effects are shown in Appendix Figure OA.22.

- $\hat{\lambda}$: To estimate the shadow price of the consumer surplus constraint, we use the fact that in equilibrium, $\lambda = \partial W/\partial CS_0$, the minimum CS required for the constraint to be satisfied. To estimate this, we calculate the change in in-sample welfare from increasing the uniform handgun tax by 0.1%, since an increase in the tax rate would represent the allowed (class-level uniform) taxes if the CS constraint were slightly more slack. We calculate $\hat{\lambda}$ as the ratio of the change in aggregate welfare to the change in consumer surplus from this small tax increase.

$$\hat{\lambda} = -\frac{W(v_h = 15.6, v_l = 0) - W(v_h = 15.5, v_l = 0)}{CS(v_h = 15.6, v_l = 0) - CS(v_h = 15.5, v_l = 0)}$$

This yields an estimate of $\hat{\lambda} = 1.8$, or for each dollar of consumer surplus lost, welfare increase by 1.12 net dollars.

- ϕ_j: As noted in the main text, we assume that marginal externality in sample is equal across all new andgun purchases. We take as given our estimated $MSC_h = \$338$/year in circulation for each handgun, and take the 4-year lifespan of the effect with no discounting over time (but allowing discounting due to depreciation). This is meant to account for the effect that a random gun stays in the circulation for 4-years during our sample (e.g. our sample is 2016-2022, covering 7 years). Explicitly:

$$\hat{\phi}_h = MSC_h \cdot \frac{1 - (1-\delta)^4}{1 - (1-\delta)}$$

  where δ is the firearms depreciation rate estimated in the public health model.

With these estimates, we start by estimating an approximation to the optimal specific tax as:

$$\hat{\tau}_{j,t} = \hat{\phi}_h - \hat{\mu}_{j,t} - \hat{\lambda} \cdot \hat{\mu}^M_{j,t} \tag{OA.23}$$

We then make a few alternations to ensure the tax scheme is implementable and comparable across years. First, because the public health effects of firearms purchases accumulate over time, we do not want our results to be driven by intertemporal substitution of taxes (for example, by implementing a very high tax in 2016, where purchases contribute to public health for seven years, and a very low tax in 2022, where effects last for one year). Mrket structure, and hence margins, also vary across years, which may lead to differences in tax rates across years. To correct for these intertemporal effects, we implement a tax scheme that is constant across years. To do this, we demean the initial calculation of the tax in Equation OA.23 by year, netting out differences attributable to year-specific changes. Call this version of the tax $\tilde{\tau}_{j,t}$. Finally, to ensure the tax can be implemented as an ad valorem tax, we scale the tax to be between 0 and 1 and set the final tax as:

$$v_{j,t} = g \cdot \frac{\tilde{\tau}_{j,t} - \min_{j,t}\{\tilde{\tau}_{j,t}\}}{\max_{j,t}\{\tilde{\tau}_{j,t}\} - \min_{j,t}\{\tilde{\tau}_{j,t}\}} \tag{OA.24}$$

where g is a hyperparameter chosen to ensure that CS does not decrease.

For the targeted handgun tax when their is no supply response, we follow the exact same procedure, except we do not include the equilibrium margin term μ_j in Equation OA.23 (e.g. $\hat{\tau}_{j,t} = \hat{\phi}_h - \hat{\lambda} \cdot \hat{\mu}^M_{j,t}$), to reflect the design of the optimal specific tax under competitive supply as in Proposition 3.

Table OA.1: States with Point of Contact and Available Data

State	Covered Firearms	Data	Background Checks	Approved Transactions	Physical Transfers	Gun Type
CA	All	Y	Y	Y	Y	Y
CO	All	Y	Y	Y	—	Y
D.C.	All	—				
FL	All	Y	Y	—	—	—
HI[1]	All	Y	Y	Y	Y	Y
IL	All	Y	Y	—	—	—
MD[2]	Handgun	Y	Y	—	—	—
NH	Handgun	—				
NJ	All	—				
NV	All	—				
OR	All	Y	Y	—	—	—
PA	All	Y	Y	—	Y	Y
TN	All	Y	Y	—	Y	Y
UT	All	Y	Y	Y	—	—
VA	All	Y	Y	—	Y	Y
WA	Handgun	—				
WI	Handgun	—				

Notes: A single transaction may involve multiple physical transfers of firearms. 1. HI POC reports that background check practices confound the mapping between background checks, transactions, and physical firearm transfers. 2. MD POC operates for handguns and "assault weapons;" however, the most transactions of "assault weapons" have been banned in MD since October 1, 2013.

state	Coefficient	SE
california	0.8907	0.0294
colorado	0.7916	0.0232
florida	1.0083	0.0724
illinois	0.9366	0.0426
maryland	0.976	0.0444
oregon	0.9052	0.0411
pennsylvania	0.9973	0.0453
tennessee	0.9791	0.0287
utah	1.0397	0.0305
virginia	1.0276	0.041
Average	0.9416	0.0129

Table OA.2: State-level Relationship between NICS Background Checks and POC Background Checks

State	Brady Exempt Date	NICS Checks	Handgun Checks	Long Gun Checks
Michigan	2006-04	-0.391	-0.861	-0.178
		(0.122)	(0.548)	(0.104)
Kentucky	2006-07	-0.408	-0.563	-0.336
		(0.183)	(0.540)	(0.165)
Kansas	2011-05	-0.200	-0.320	-0.151
		(0.151)	(0.176)	(0.171)
Nevada	2011-09	-0.347	-0.379	-0.418
		(0.121)	(0.118)	(0.168)
West Virginia	2014-06	-0.180	-0.216	-0.154
		(0.111)	(0.369)	(0.271)
Louisiana	2015-04	-0.136	-0.138	-0.151
		(0.128)	(0.318)	(0.240)
Alabama	2016-03	-0.683	-0.760	-0.593
		(0.128)	(0.256)	(0.151)
South Dakota	2017-03	-0.223	-0.181	-0.215
		(0.110)	(0.150)	(0.124)
Minnesota	2017-05	-0.260	-0.397	-0.153
		(0.064)	(0.084)	(0.083)
Oklahoma	2023-06	-0.008	-0.002	-0.063
		(0.107)	(0.165)	(0.108)
Average		-0.296	-0.400	-0.258
		(0.062)	(0.085)	(0.055)

Table OA.3: Estimated Effects of Introducing Brady Exempt Permits on NICS Background Checks

State	Partial Permit POC End	Handgun Checks	Long Gun Checks
New York	2004-09	0.194	0.080
		(0.069)	(0.060)
Michigan	2012-12	2.009	-0.164
		(0.360)	(0.156)
Iowa	2021-07	2.686	0.104
		(0.103)	(0.079)
Average		1.836	-0.082
		(0.087)	(0.056)

Table OA.4: Estimated Effects of Ending Partial Permit POC Status on NICS Background Checks

	(1)	(2)	(3)	(4)
	1-digit	2-digit	4-digit	6-digit
Log(MSRP)	-1.797**	-2.142**	-2.565***	-2.491***
	(0.875)	(0.888)	(0.858)	(0.828)
Observations	2457	2457	2457	2457
Gun Model FE	Yes	Yes	Yes	Yes
Year FE	Class x Year	Class x Year	Class x Year	Class x Year
# Potential Instruments	132	792	2376	3366
# Selected Instruments	5	4	5	6
Sup-Score Test Statistic	12.41	12.47	12.55	12.55
First Stage Sig. (p-value)	0.0000	0.0000	0.0000	0.0000
Method	IVLASSO	IVLASSO	IVLASSO	IVLASSO

Table OA.5: Estimated Price Elasticity using Different Aggregations of commodities

Table displays the estimated own-price elasticity of demand from the IVLASSO routine described in Section 4.1. The sample in this table is restricted to guns with at least 100 purchases in Massachusetts from 2016-2022. Columns vary in the fidelity of the price indices used. Column (1) reports the estimates using 1-digit commodity indices (2 price indices), Column (2) 2-digit (12 indices), Column (3) four-digit (36 indices), and Column (4) 6-digit (51 indices). Each estimate includes gun model and class-year fixed effects. Standard errors in parentheses are robust to heterogeneity. * denotes $p < .1$, ** denotes $p < .05$, *** denotes $p < .01$.

Consumer Characteristic:	Baseline	Female	Frac White	Frac Conservative	Log(Median Inc)	Log(Density)	Nesting Parameter (ρ)	Random Coef. (σ)
Handgun (vs No Gun)	-0.720***	-1.092***	0.822***	1.019***	-0.637***	-0.089***	0.893*	
	(0.004)	(0.034)	(0.040)	(0.037)	(0.012)	(0.002)	(0.074)	
Long gun (vs Handgun)	-0.182***	-0.738***	0.640***	0.230***	-0.192***	-0.006***	0.240***	
	(0.005)	(0.069)	(0.068)	(0.029)	(0.021)	(0.001)	(0.006)	
Shotgun (vs Rifle)	-0.224***	-0.147***	0.015	-0.210***	0.658***	0.049***		0.011
	(0.006)	(0.014)	(0.033)	(0.041)	(0.018)	(0.003)		(1.790)
Used Gun (vs New for $0)	1.155***	-0.767***	0.502***	0.397***	0.248***	0.012***		0.083
	(0.023)	(0.022)	(0.028)	(0.032)	(0.011)	(0.002)		(0.077)
Caliber (In.)	0.178***	-0.200***	0.222***	0.499***	-0.135***	-0.044***		0.001
	(0.012)	(0.025)	(0.062)	(0.080)	(0.023)	(0.005)		(29.277)
Barrel Length (Ft.)	0.109***	-0.122***	0.215***	0.009	-0.355***	-0.008***		0.002
	(0.004)	(0.007)	(0.013)	(0.013)	(0.009)	(0.001)		(1.969)
High Capacity Weapon	0.082***	-0.109***	-0.163***	0.021**	0.138***	0.008***		0.014
	(0.002)	(0.005)	(0.010)	(0.010)	(0.005)	(0.001)		(0.340)
Price Coef. (Multiplier)	-0.103***	0.773***	-0.285***	-0.471***	-0.620***	-0.044***		0.437***
	(0.028)	(0.010)	(0.016)	(0.023)	(0.008)	(0.001)		(0.008)

Table displays estimates of the non-linear parameters of our demand model. Standard errors are in parantheses and calculated using corrected formula for constrained maximum likelihood described in Moore et al. (2008). Stars indicate statistical significance of p-values. For all parameters θ except the nesting parameters (ρ_0, ρ_c), this is the $Pr(\theta) = 0$; for ρ_0, this is $Pr(\rho_0 < 1)$; for ρ_c, this is $Pr(\rho_c < \rho_0)$. In brackets, we display p-values for the following tests: for ρ_0, the test that $\rho_0 \leq 1$, for ρ_c, the test that $\rho_c \leq \rho_0$, and for ρ_c^u, the test that $\rho_c^u \leq \rho_c$. These significance tests are performed using a one-sided z-score test, treating the upper bound of the test as a known number.
* denotes $p < .1$, ** denotes $p < .05$, *** denotes $p < .01$,

Table OA.6: Demand Parameters

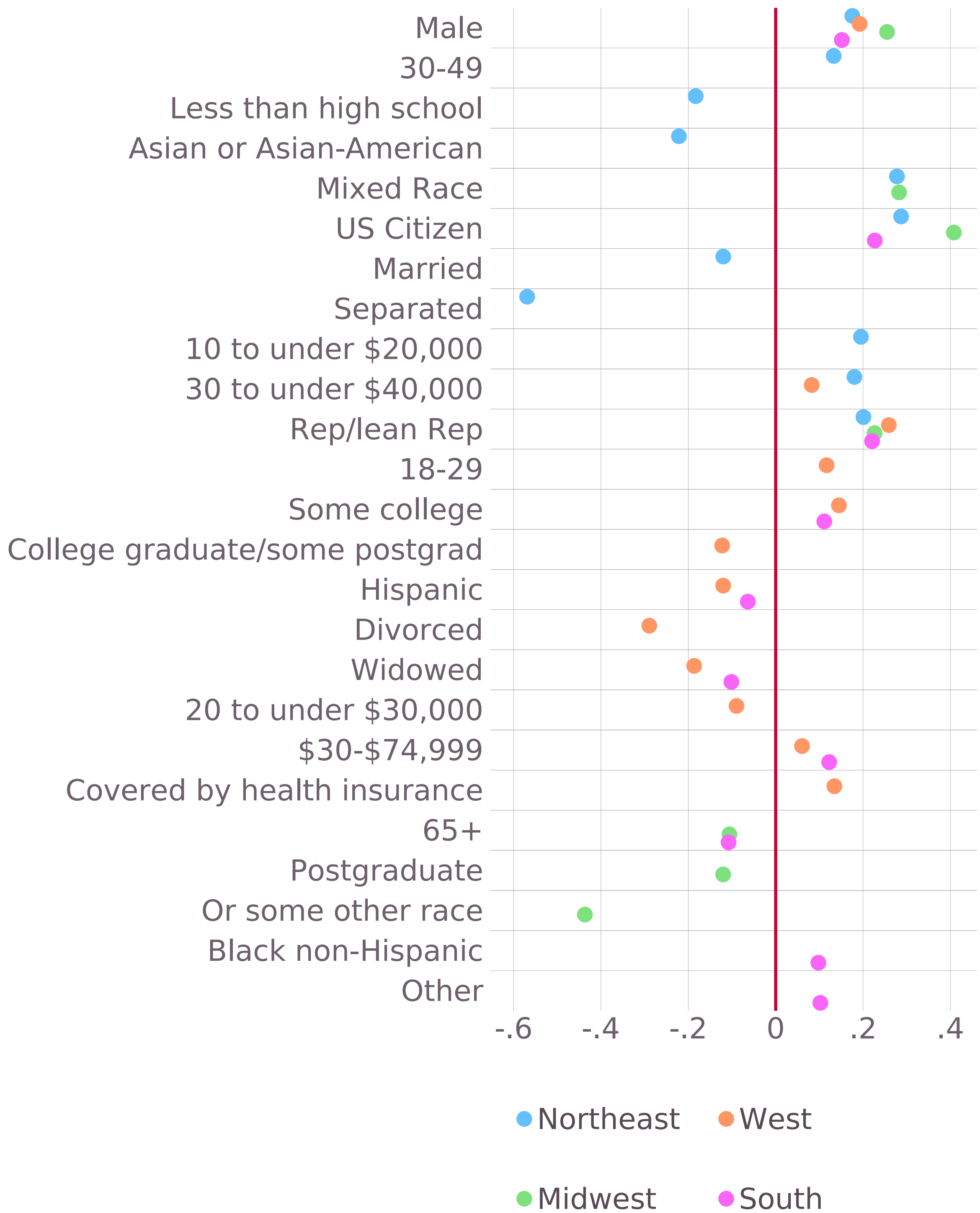


Figure OA.1: Estimated Lasso Coefficients for Predicting Market Size, From Pew's American Trends Panel

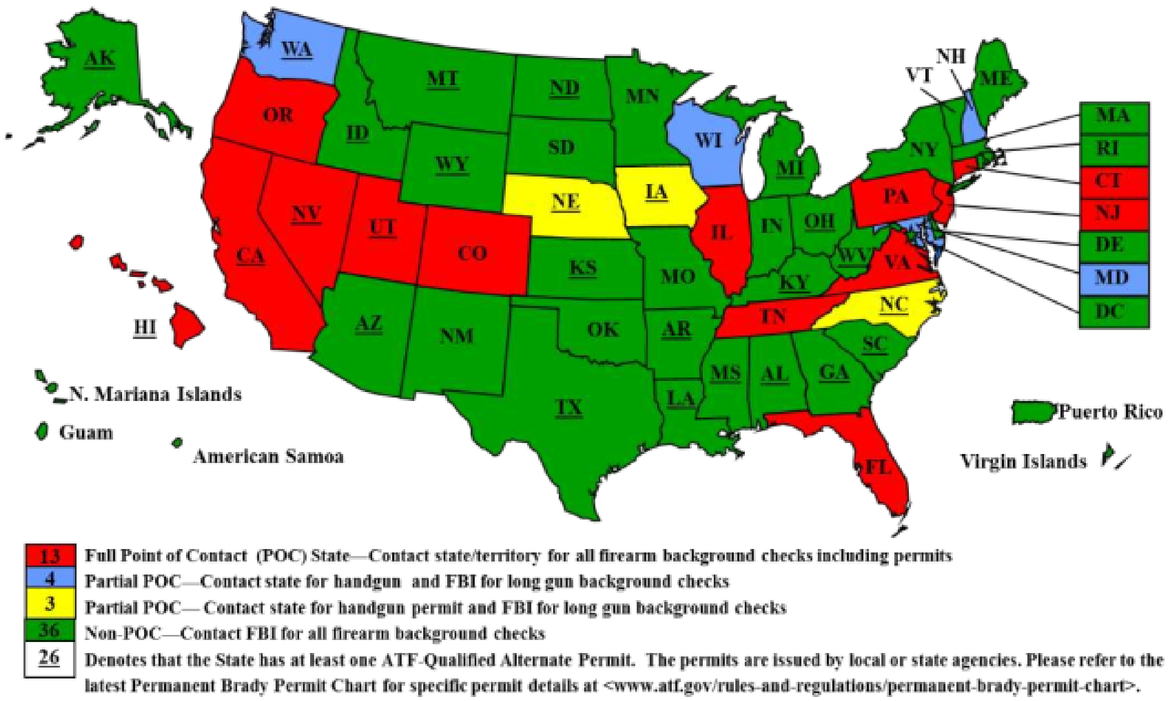


Figure OA.2: POC and Brady Exemptions by State, 2016

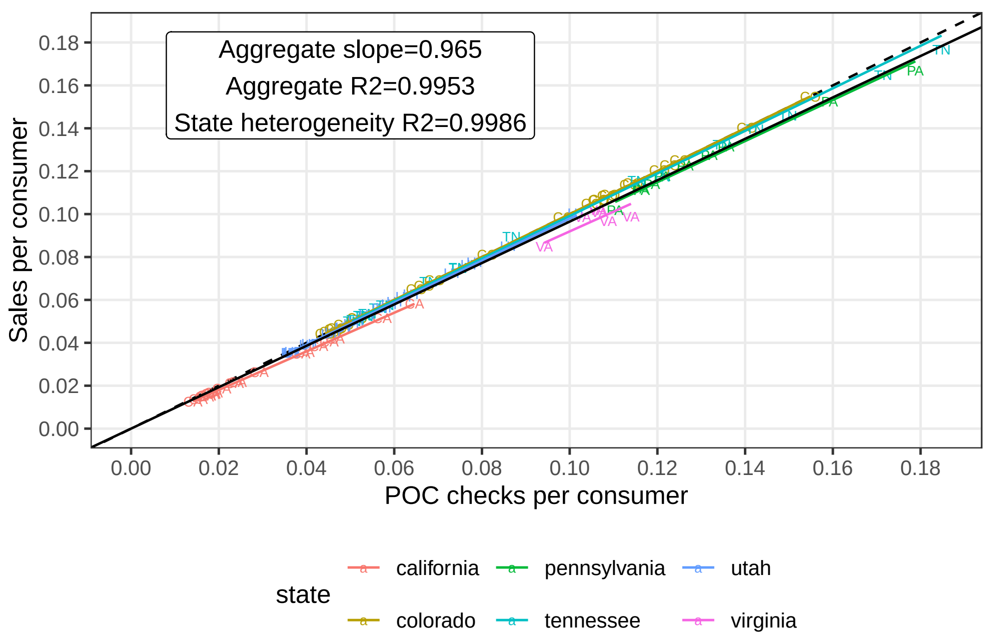


Figure OA.3: Relationship between POC Background Checks and Physical Firearm Transfers

Notes: We observe physical firearm transfers in CA, PA, TN, and VA. In CO and UT, where we do not observe physical transfers, we estimate physical firearm transfers as physical transfers = 1.1 × approved firearm transfers. Although we observe physical transfers in HI, we do not observe POC checks in that state. All regression statistics are computed in logs.

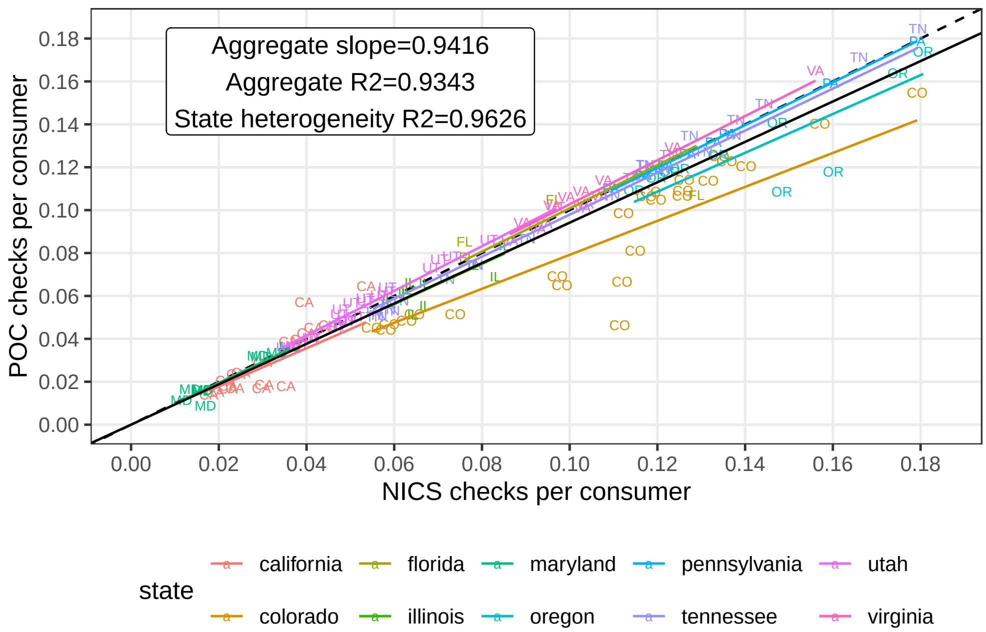


Figure OA.4: Relationship between NICS and POC Background Checks

Notes: All regression statistics are computed in logs.

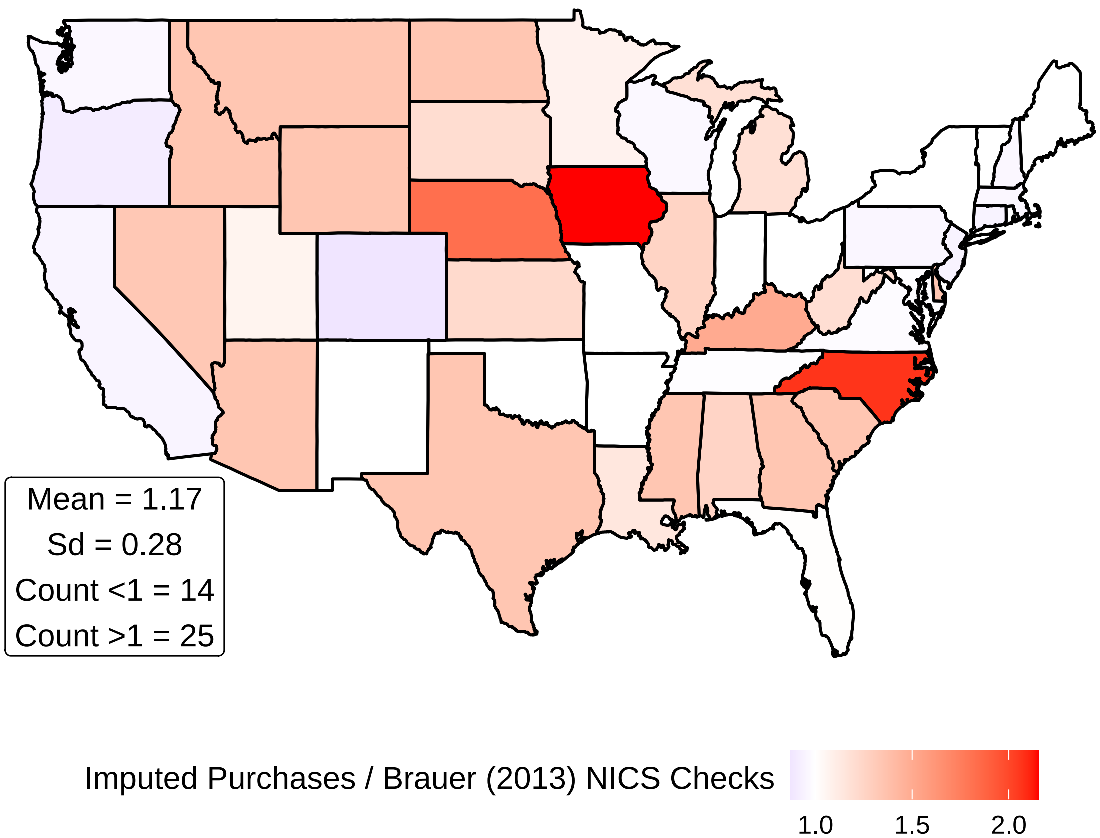


Figure OA.5: Ratio of Adjusted NICS Background Checks to Unadjusted NICS Background Checks, 2016-2022, by State

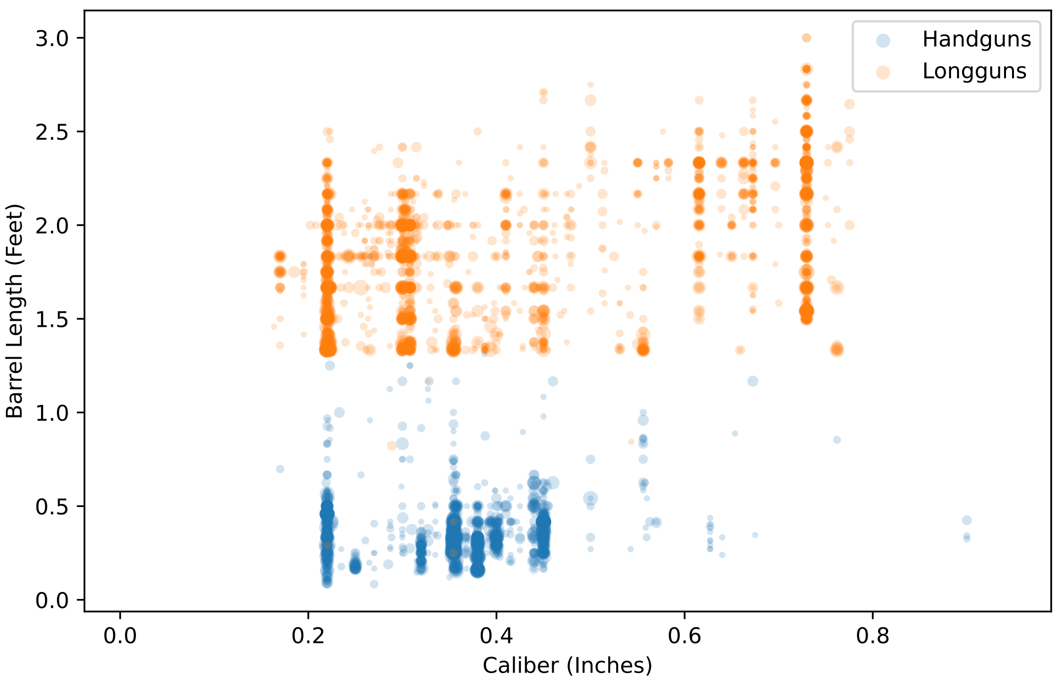
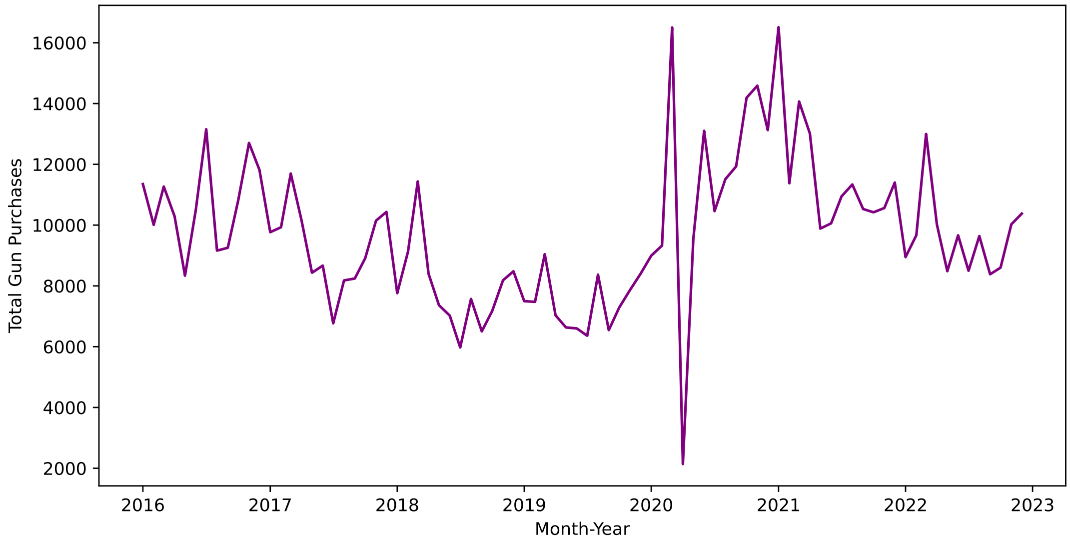
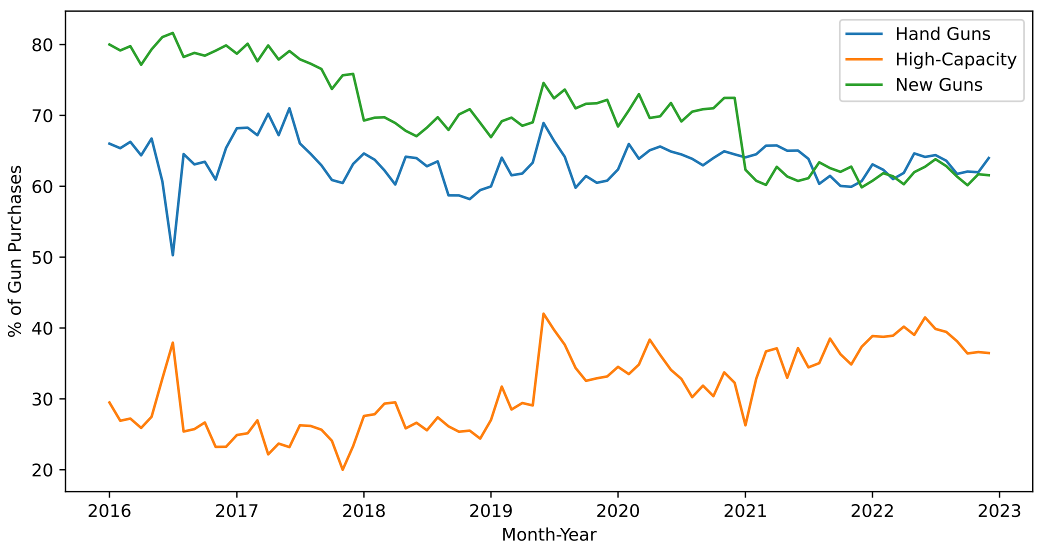


Figure OA.6: Caliber and Barrel Length Distribution Across Gun models

Figure displays the distribution of gun models by caliber (in inches) and barrel length (in feet), split by weapon class. Each model's dot size is proportional to the the number of units sold in Massachusetts from 2016-2022.



(a) Aggregate Gun Purchases Over Time



(b) Composition of Purchases Over Time

Figure OA.7: Firearm Purchase Trends in Massachusetts

Figure displays the time series of gun purchases in Massachusetts from 2016-2022. Panel (a) displays the total number of gun purchases each month, while Panel (b) displays the composition of these purchases by weapon class. Hand guns refers to those transactions classified as a handgun in the FRB data. For new gun and high-capacity weapon, these characteristics are only defined for guns we match to the blue book data, so we divide by the total number of purchases matched to a blue book gun in each month.

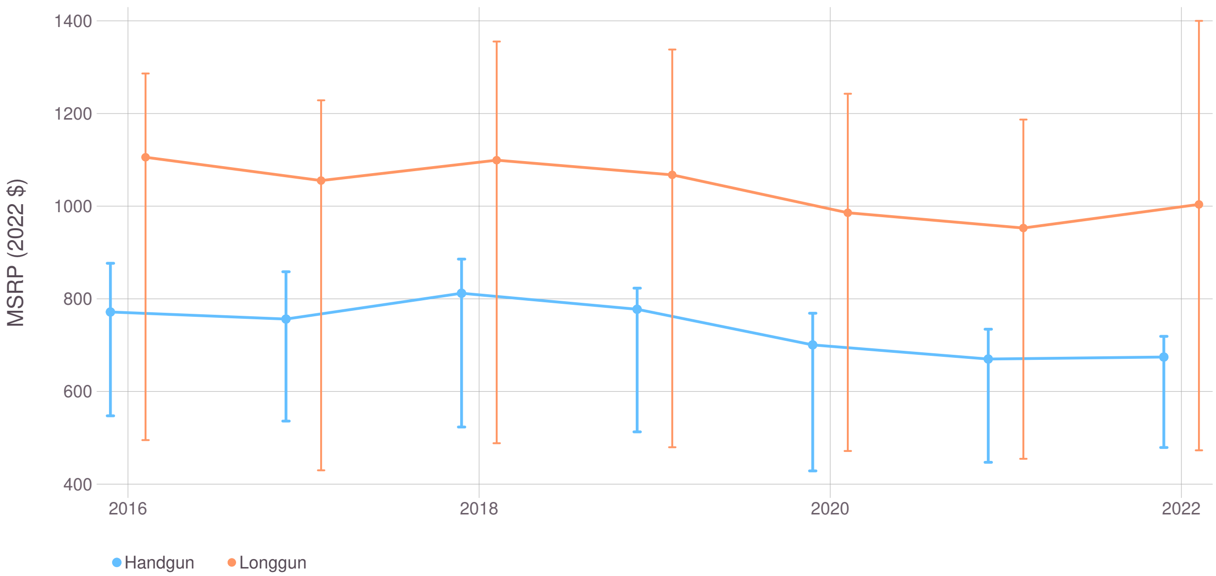


Figure OA.8: New Gun Prices over Time

Figure displays the Manufacturer's Suggested Retail Price (MSRP) of guns in active production that we match to the Massachusetts microdata, by weapon class. dots indicate the mean price of a new purchased gun in each year, while error bars indicate the interquartile range.

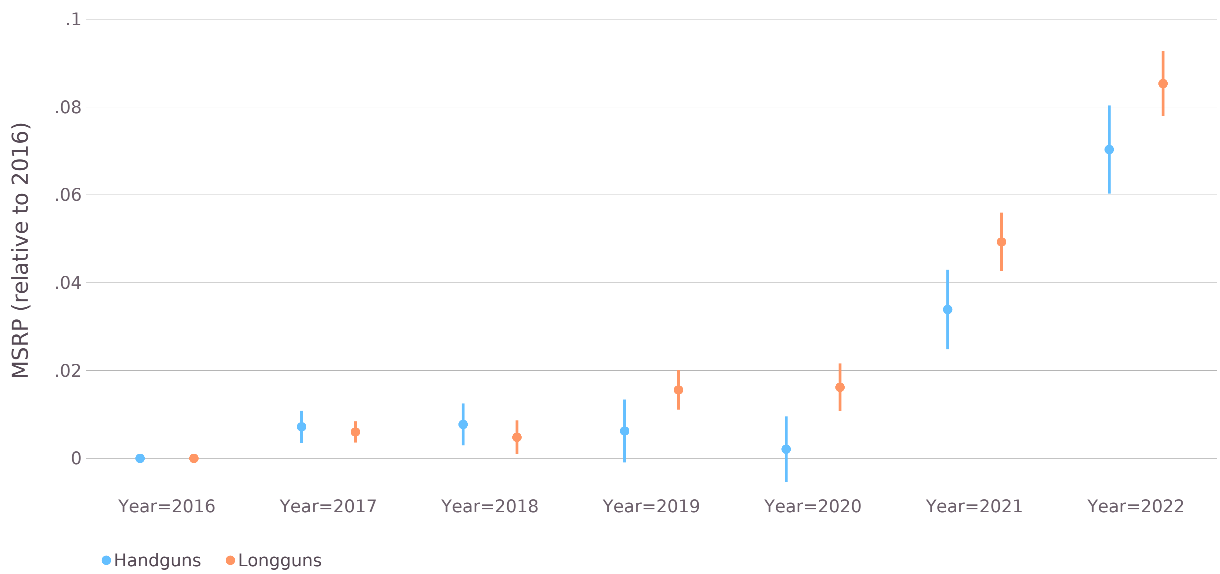


Figure OA.9: New Gun Prices over Time (Controlling for Variety)

Figure displays estimates from a regression of log(MSRP) of new gun models we match to the Massachusetts FRB microdata by year (relative to 2016), controlling for class-year and firearm model fixed effects.

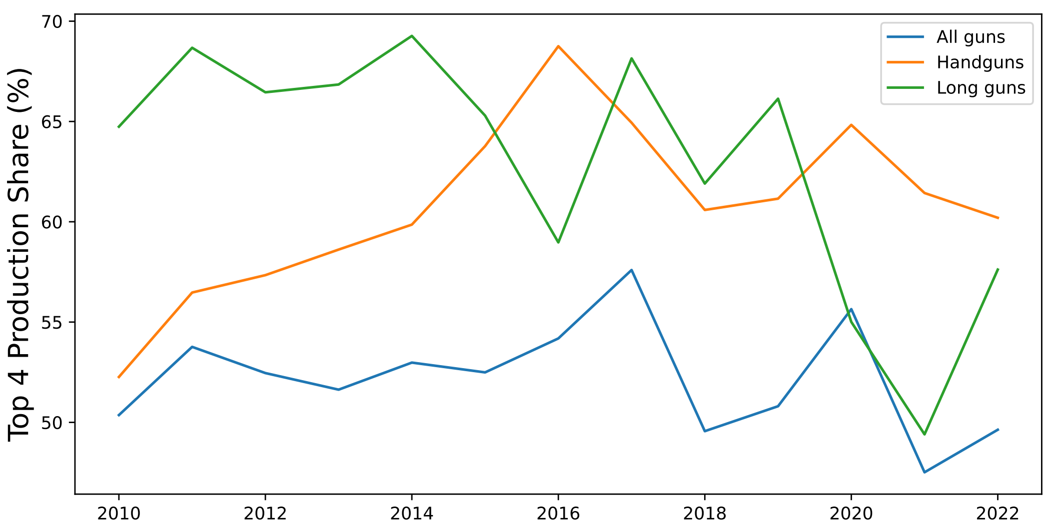


Figure OA.10: Concentration in the U.S. firearms industry

Figure displays the yearly share of the four largest firms in the production of all firearms and separately for handguns and long guns.

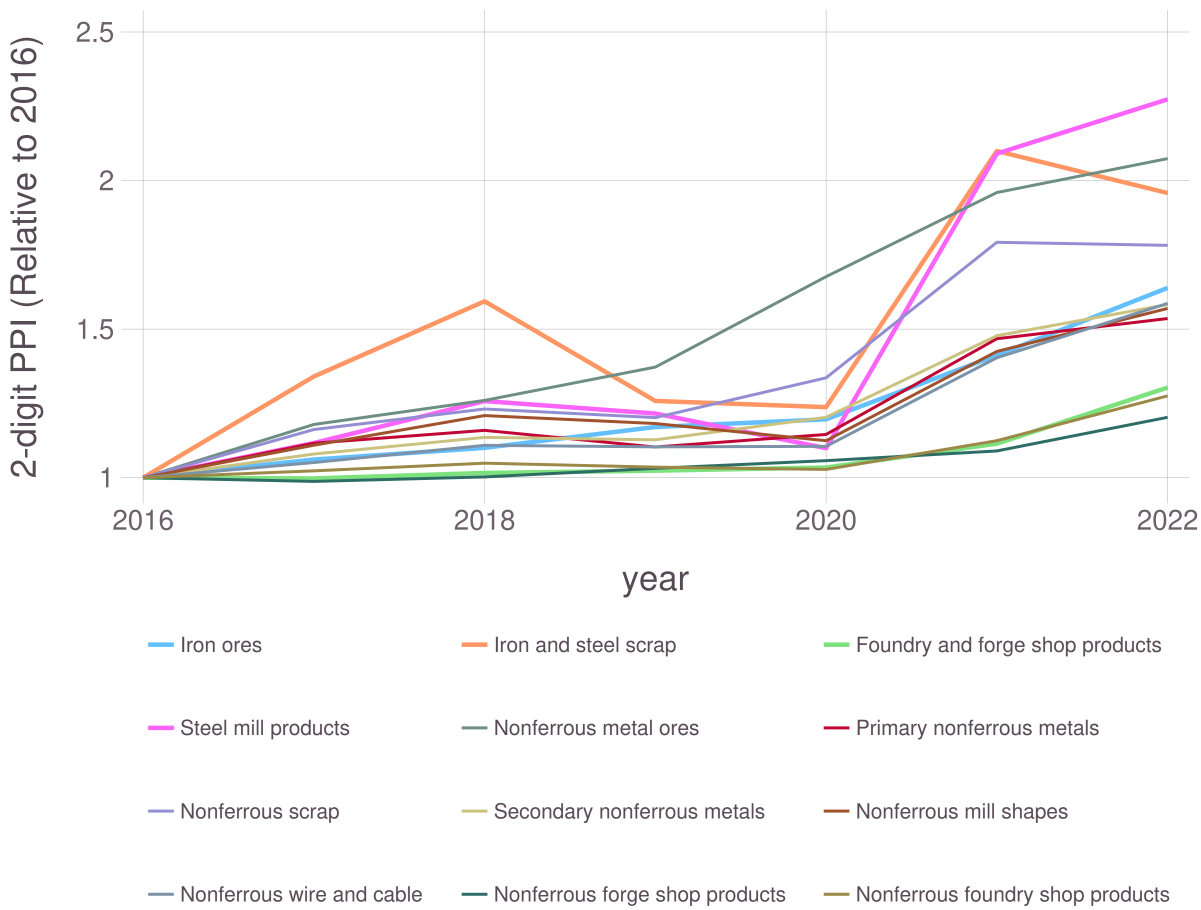


Figure OA.11: Time Series of Annual Price Indices for Firearms Production Inputs

Figure shows the annual time series of all 2-digit primary metal commodity PPIs, from the Bureau of Labor Statistics. The PPIs are normalized to be 1 in 2016.

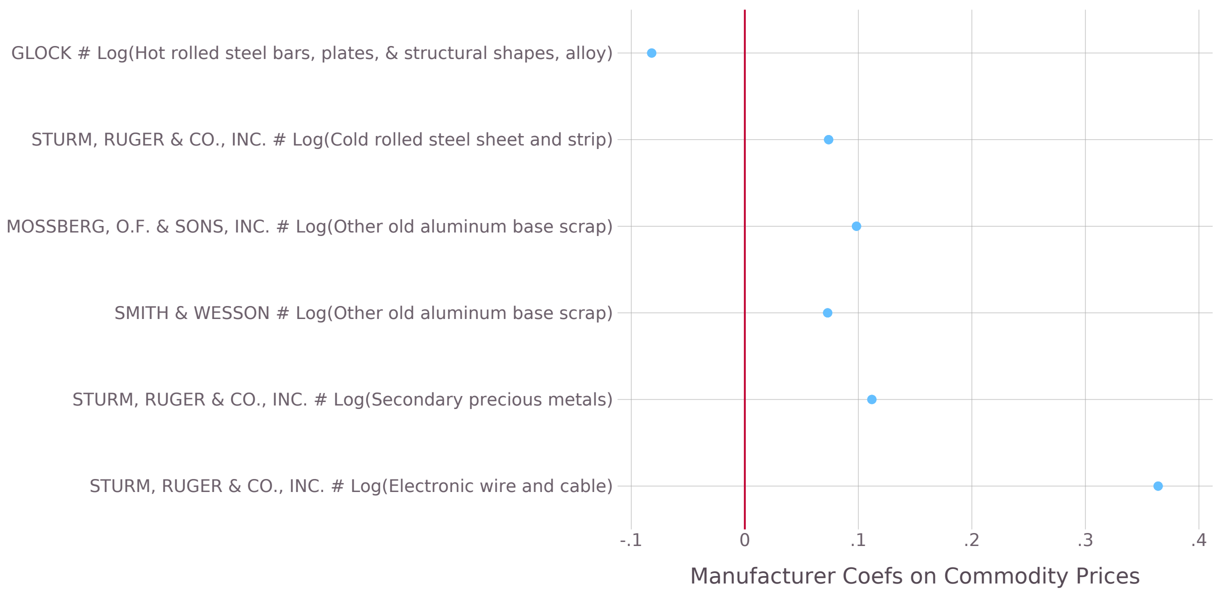
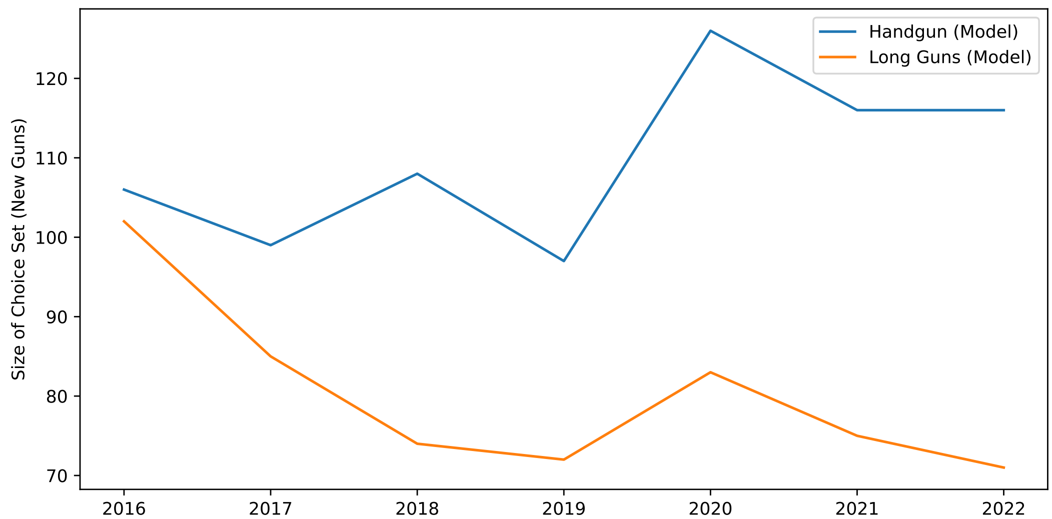
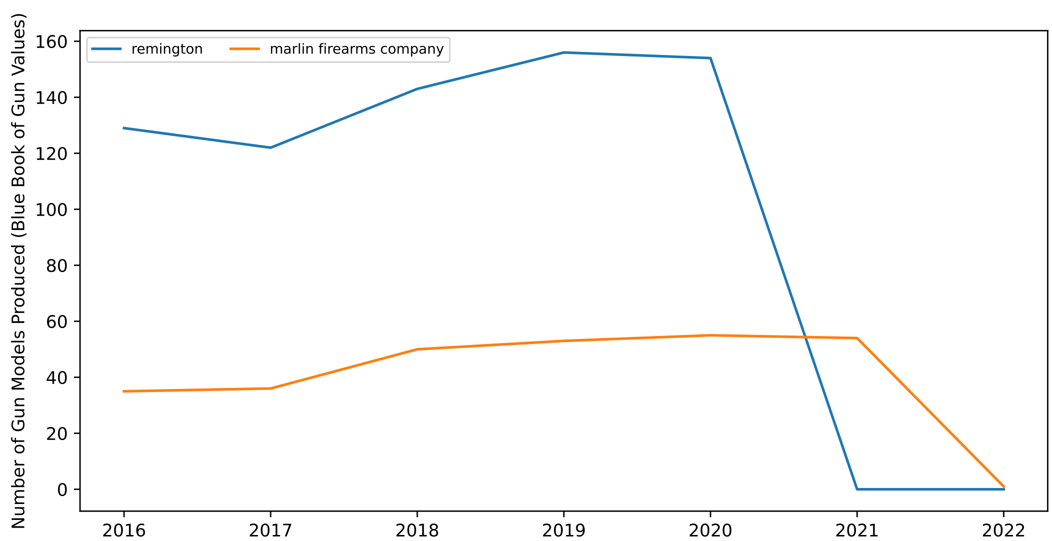


Figure OA.12: Estimated Non-Zero coefficients for IVLASSO of Prices

Note: Figure plots the magnitude of the selected coefficients from a lasso of log(MSRP) on logged commodity prices interacted with an ID for manufacturer, with gun model and weapon class times year fixed effects.coefficients.



(a) Choice sets $\mathcal{J}_{c,t}$ by Weapon Class and Year



(b) Case Example: Remington's Exit from Firearm Production

Figure OA.13: Choice Sets in Demand Model over Time

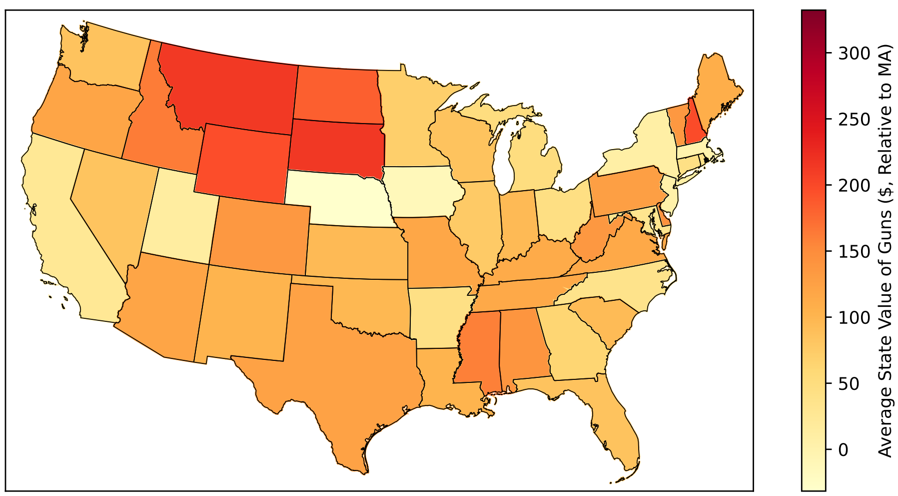
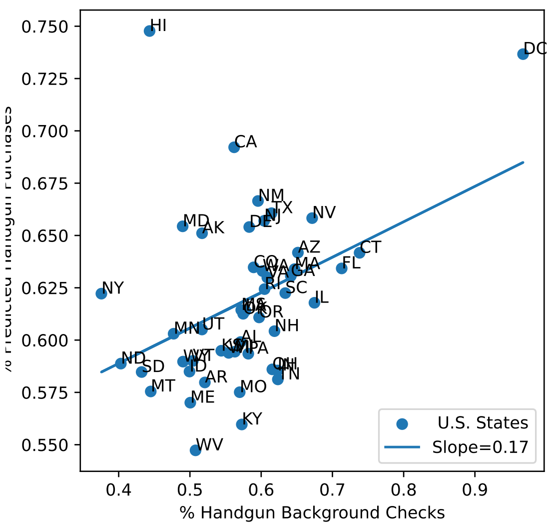
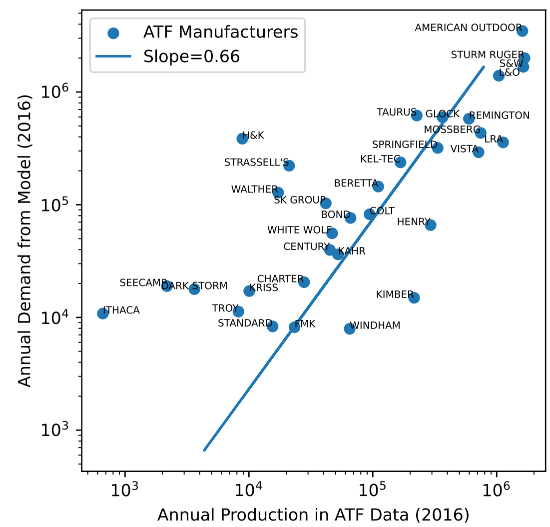


Figure OA.14: Average State-year Taste Shifters for Firearms by State , in $

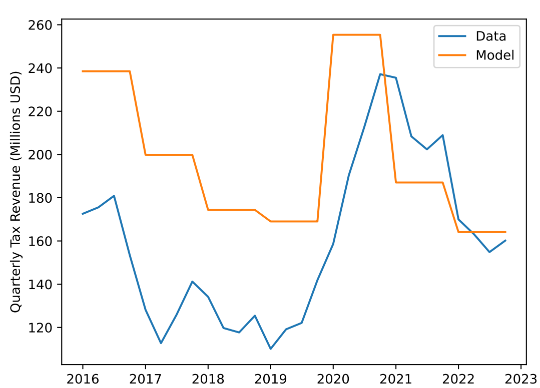
Figure shows the average value of $E[CS_{i,t}] - E[CS_{i,t}|\tau = 0]$ for each U.S. state s from 2016-2022, to express the differences in willingness-to-pay for firearms across markets in dollar terms.



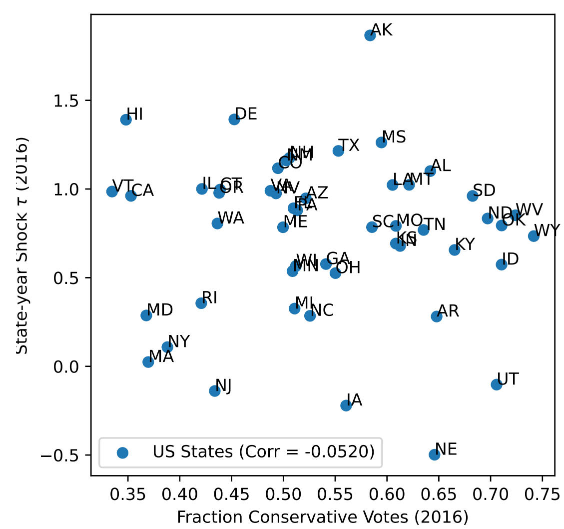
(a) % Handgun Sales by State (Model vs NICS Data)



(b) 2016 Sales by Domestic Firms (Model vs ATF Production Data)



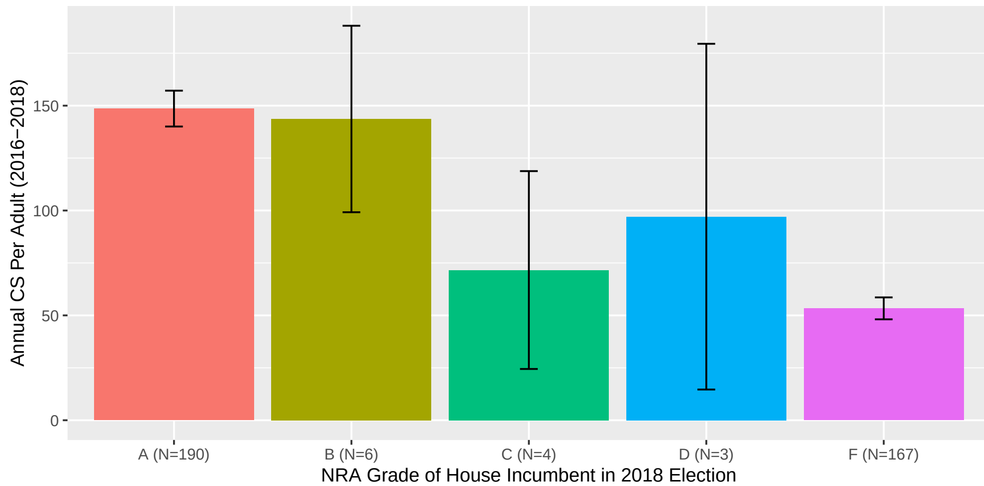
(c) Excise Tax Revenue by Quarter (Model vs FAET Filings)



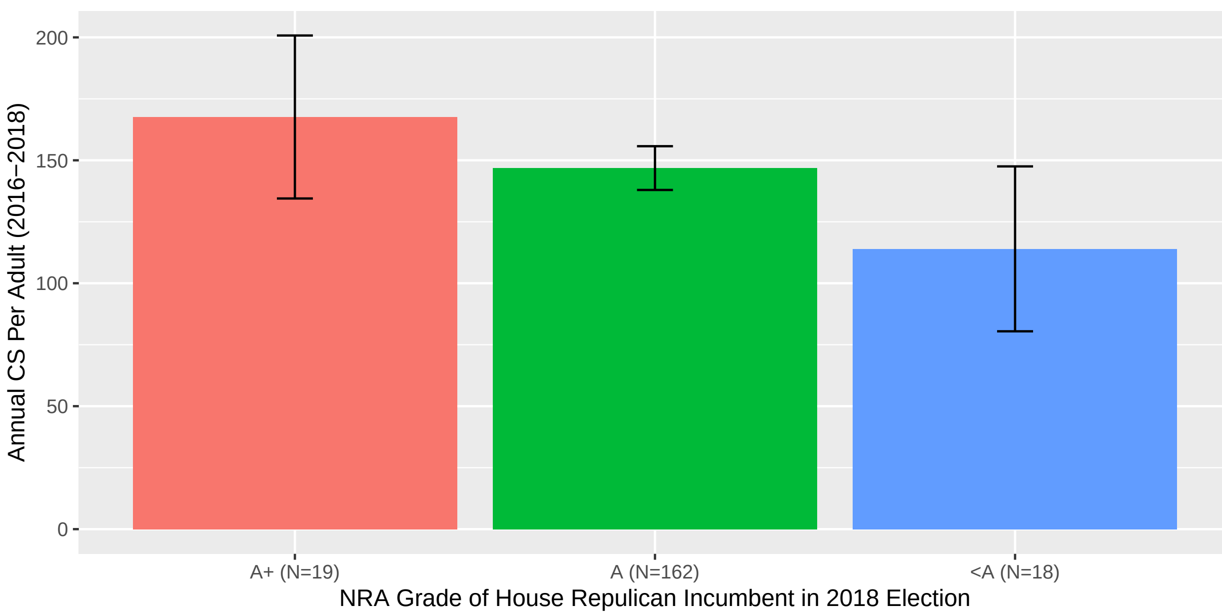
(d) % Conservative vs State-year Shock (2016)

Figure OA.15: Out-of-Sample Moments of National Demand vs Structural Model

Panel (a) displays the proportion of NICS background checks attributable to handgun purchases on average, compared to the predicted % of all gun purchases that are handguns, according to our demand model. Panel (b) displays the predicted quantity of guns from our demand model in 2016 purchased from each manufacturer, compared to the observed number of guns produced by these manufacturers in 2016. Both panels have an OLS prediction line with the estimated slope. Panel (c) displays the predicted quarterly tax revenue from the model (we divide the implied annual revenue by 4), compared to the actual revenue collected by the FAET. Panel (d) displays the fraction of votes for conservative candidates against the state-level demand shock estimated from our model in 2016.



(a) NRA Grades for Incumbent Congress Members

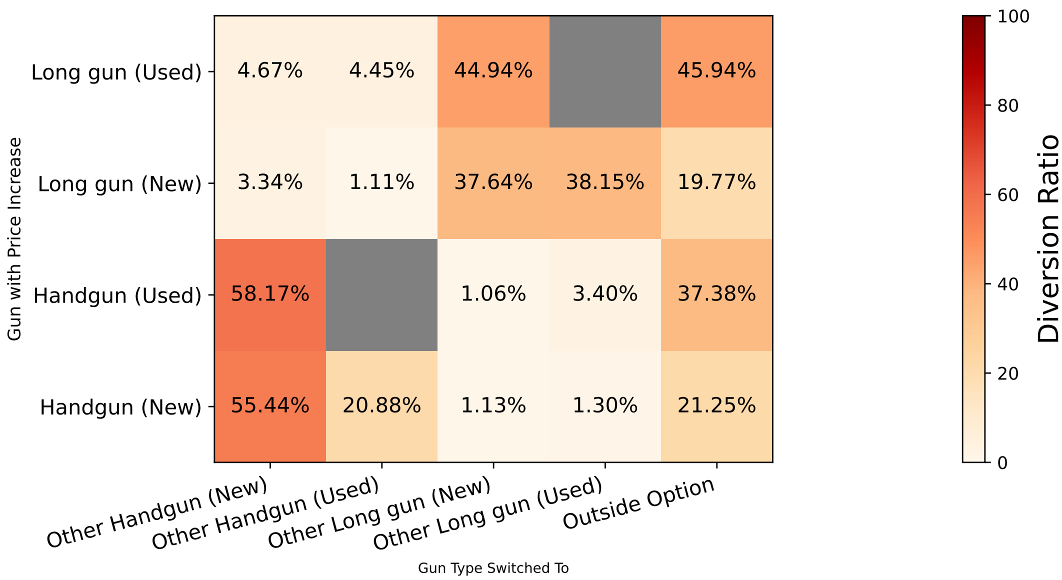


(b) Consumer Surplus and NRA Congressional Grades, Among Republican Seats

Figure OA.16: Consumer Surplus and NRA Grades

Figure shows the relationship between NRA grades of congressional members and their constituent's consumer surplus from the firearm industry. Panel A displays the average consumer surplus per adult, partitioned by the NRA grade given to their House representatives from 2017-2018, running for re-election in 2018. Figure displays the average consumer surplus per adult by congressional district from 2016-2018, among Republican-controlled seats, partitioned by the NRA grade given to their House representatives from 2017-2018, running for re-election in 2018. Figure only includes districts for which grades are given to the incumbents (85%).

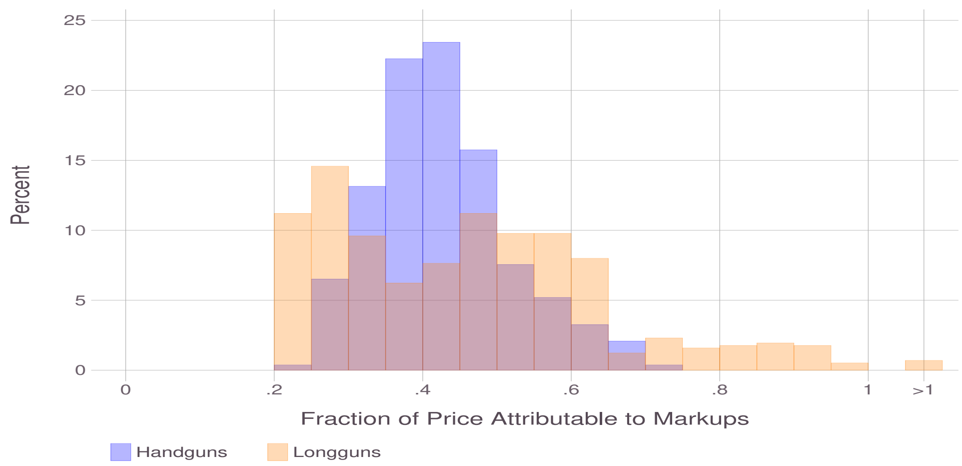
(a) Distribution of National Own-Price Elasticities, by Gun Class



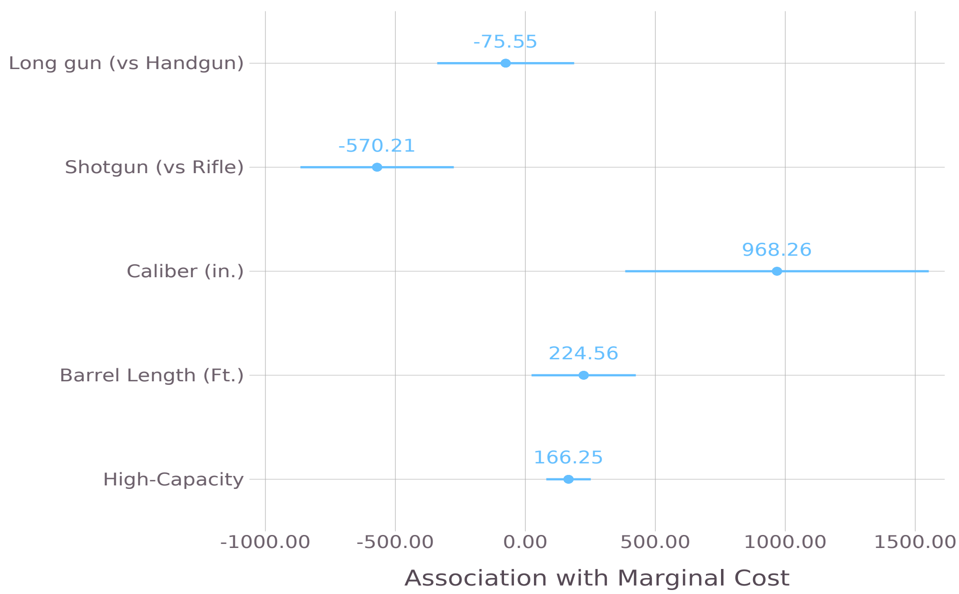
(b) National Substitution Patterns (Diversion Ratios) across Gun Types

Figure OA.17: Own and Cross Firearm Substitution Patterns

Panel (a) displays the distribution of own-price elasticities across new guns, split by weapon class. Panel (b) displays the average diversion ratio across gun types, defined as $-(\sum_{k\in G,k\neq j}\partial dq_{k,t}/dp_{j,t})/(\partial q_{j,t}/\partial p_{j,t})$ for each group G. Diversion ratios are weighted by the quantity associated with each gun model sold within group.



(a) Distribution of Lerner Indices, by Gun Class



(b) Correlates of Marginal Costs with Gun Characteristics

Figure OA.18: Marginal cost estimates

Panel (a) displays the distribution of estimated Lerner indices, defined as $(p_{j,t}(1 - v_j) - c_{j,t})\,/p_{jt}$, the share of revenue from a firearm sale taken as profit by manufacturers, split by weapon class. Panel (b) displays the estimated correlates of marginal cost from the following two-step regression:

$$
\begin{aligned}
c_{j,t} &= c_j + \delta_y + \epsilon^c_{j,t} \\
c_j &= \beta X_j + \epsilon^c_j
\end{aligned}
$$

Where the second regression is estimated via GLS with weights proportional to the variance of the estimated fixed effects.

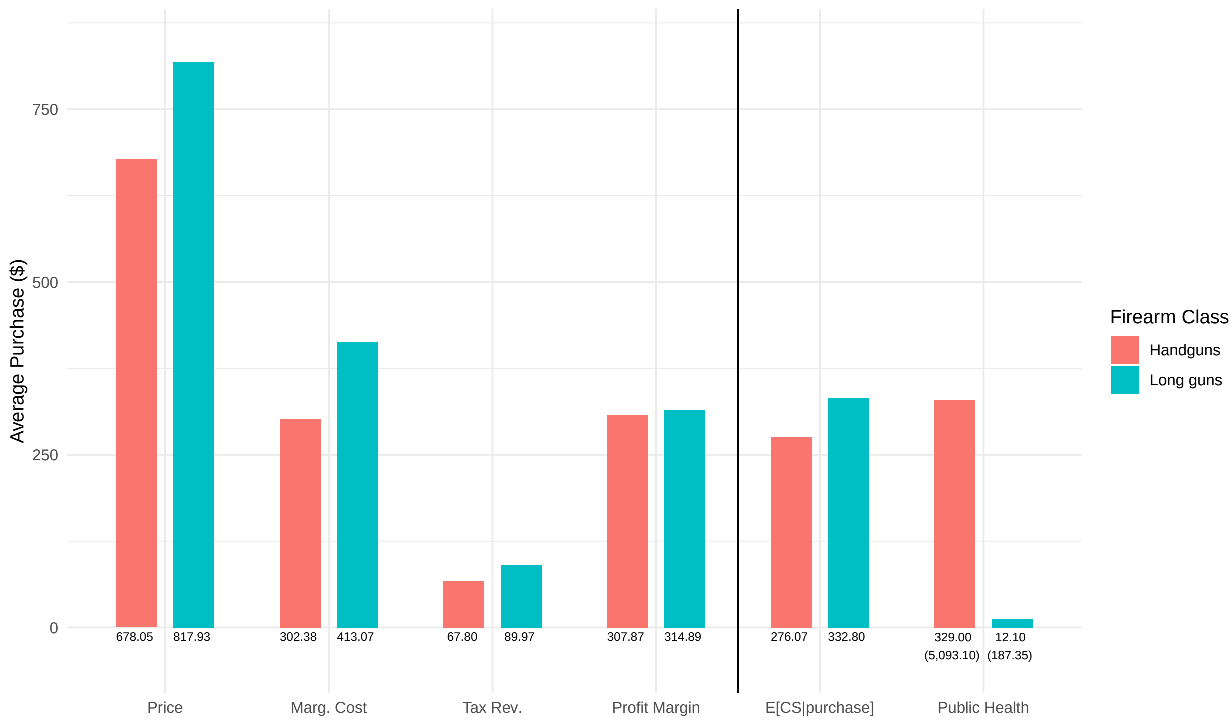
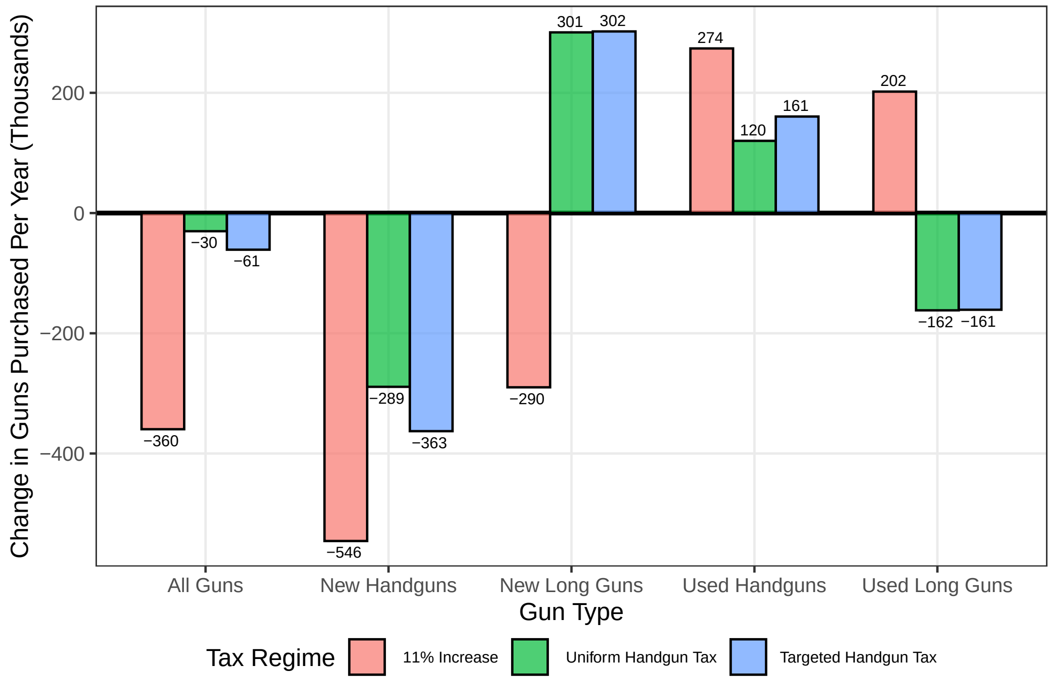
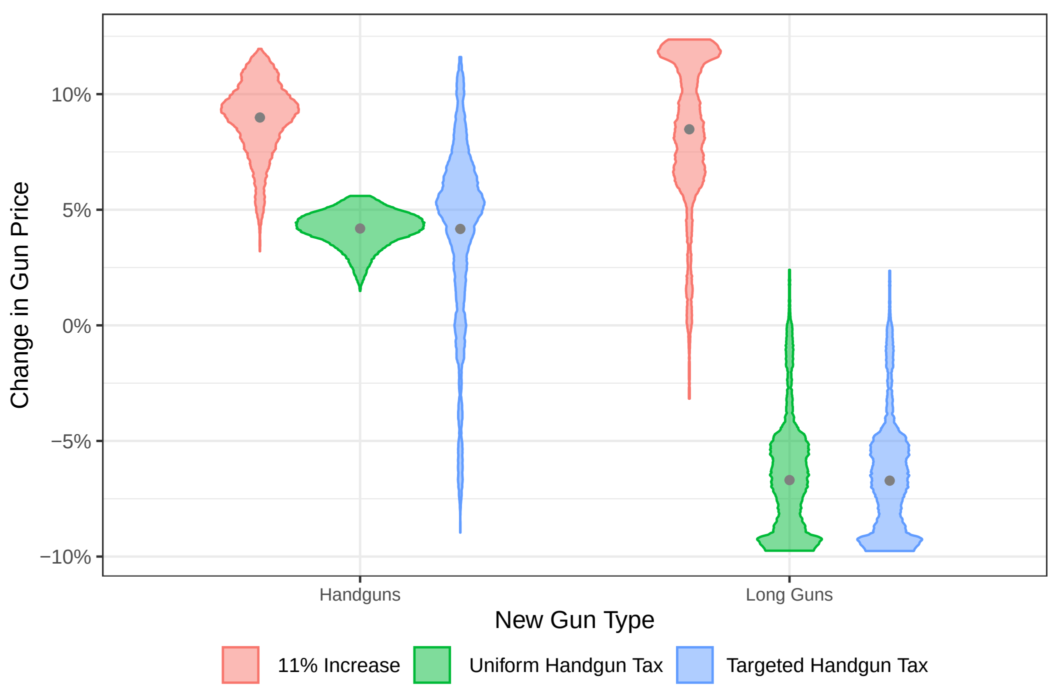


Figure OA.19: Distribution of Surplus from Firearm Purchase

Figure displays distribution of surplus from an additional firearm purchase, by firearm class, weighted by model-predicted firearm purchase quantities in the U.S. between 2016–2022. Bars are the average of a statistic across firearm-years within a class. Price is the firearm's MSRP. Tax Revenue is the revenue to the federal government generated by the firearm's sale under status quo regulation $v_j p_{jt}$. Marginal cost is our estimate of the marginal production cost c_{jt}. Profit margin is our estimate of price, less taxes and marginal cost $p_{jt}(1 - v_j) - c_{jt}$. By construction, the sum of tax revenue, marginal cost, and profit margin equals the price. Consumer surplus measures the average value across consumers of purchasing each firearm, conditional on that firearm being the best alternative in their choice set. Public health is equal to the dollar value of homicides expected to be generated by a firearm one year after its purchase (i.e., a taller bar represents more damage from homicides). The net present value of the expected lifetime public health cost of a firearm purchase is in parentheses.



(a) Change in Purchases by Gun Type



(b) Change in Prices

Figure OA.20: Effects of Firearms Tax Policies on Prices and Quantities

Figure shows changes in prices and quantities from the different tax policies we consider. In Panel (a), we show the aggregate change in gun sales by year, by type of firearm. In Panel (b), we display a violin plot of the distribution of the change in gun prices by product, among new guns. The dot in each density plot represents the average percentage change in prices, by weapon class. The horizontal lines shows the implied change if price were equal to marginal cost, as a benchmark.

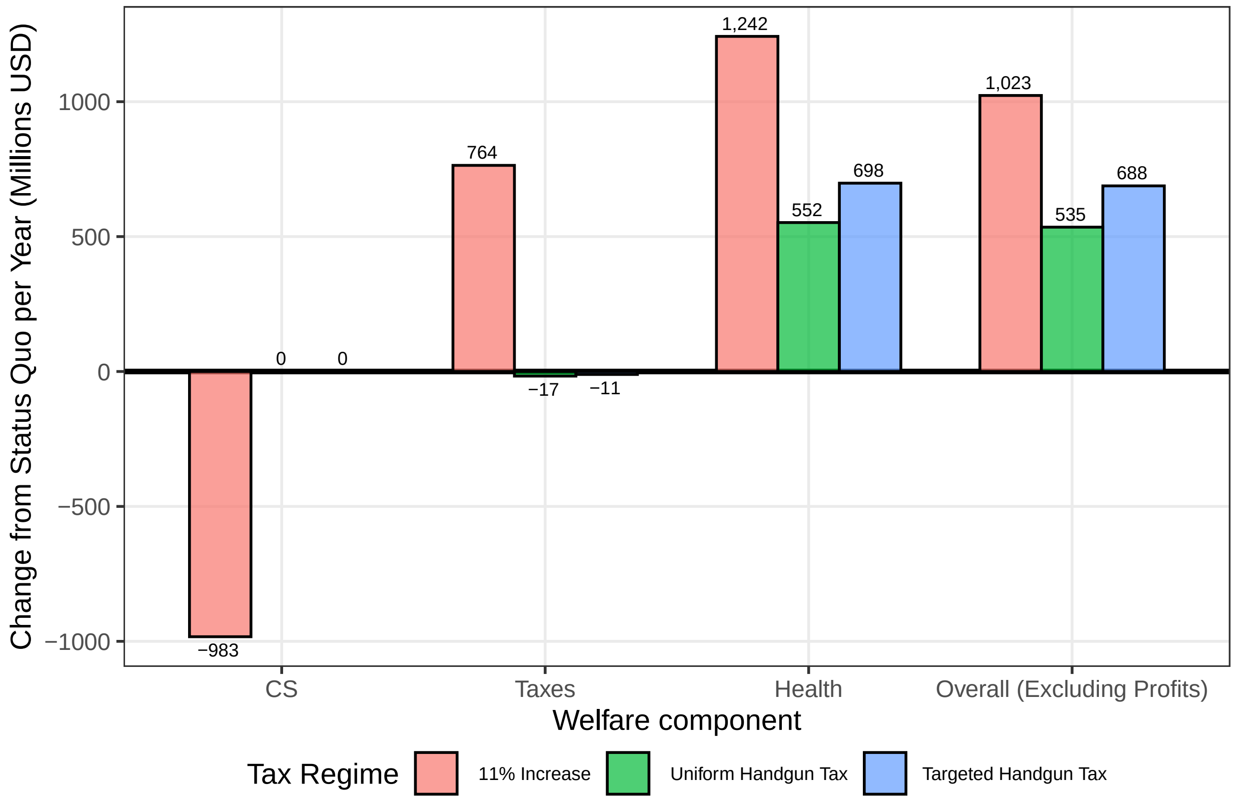


Figure OA.21: Welfare Effects of Firearms Tax Policies Under Competitive Pricing

Figure shows the average annual welfare effects of different tax policies in the U.S. during our sample, broken down by welfare components, assuming that manufacturers of new guns set prices at marginal cost.

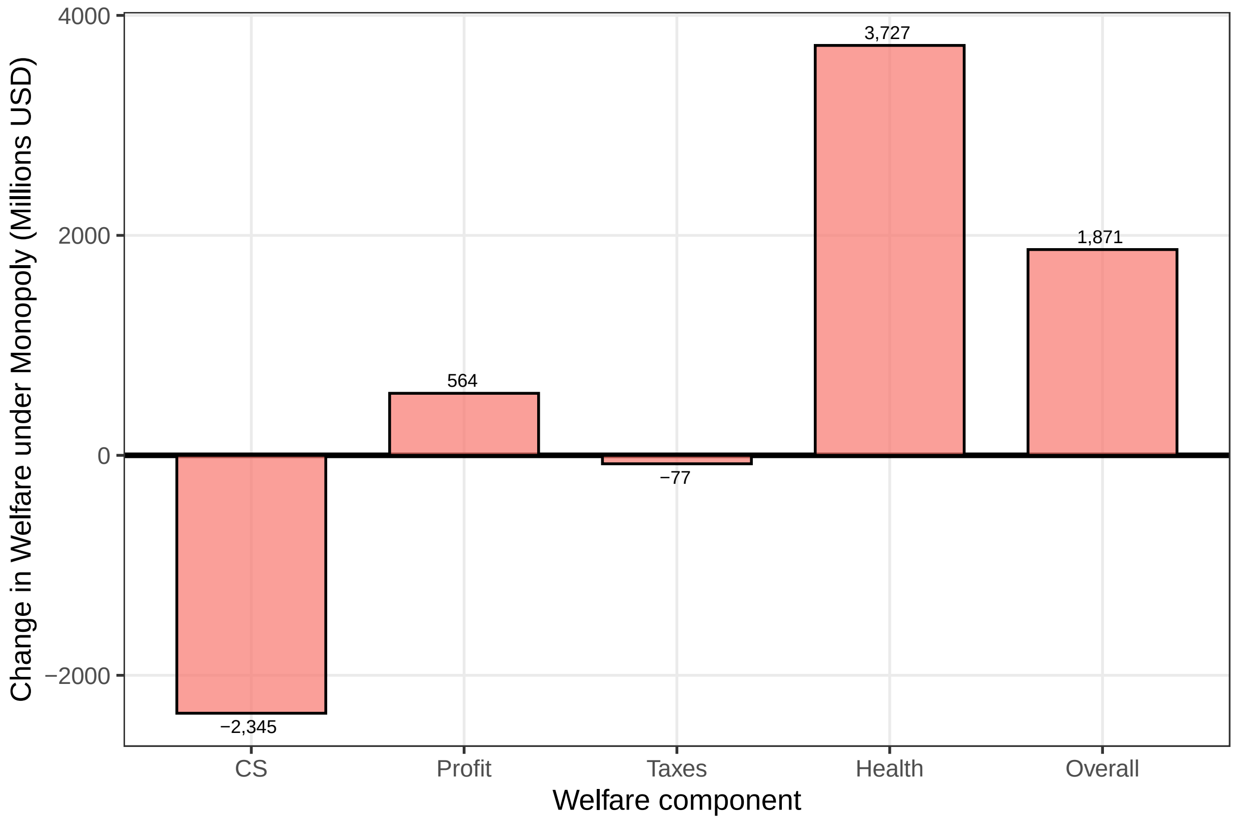


Figure OA.22: Welfare Effects of Monopoly Pricing

Figure shows the average annual welfare effects of different tax policies in the U.S. during our sample, broken down by welfare components, assuming that all firearm manufacturers are owned by a single firm and coordinate.

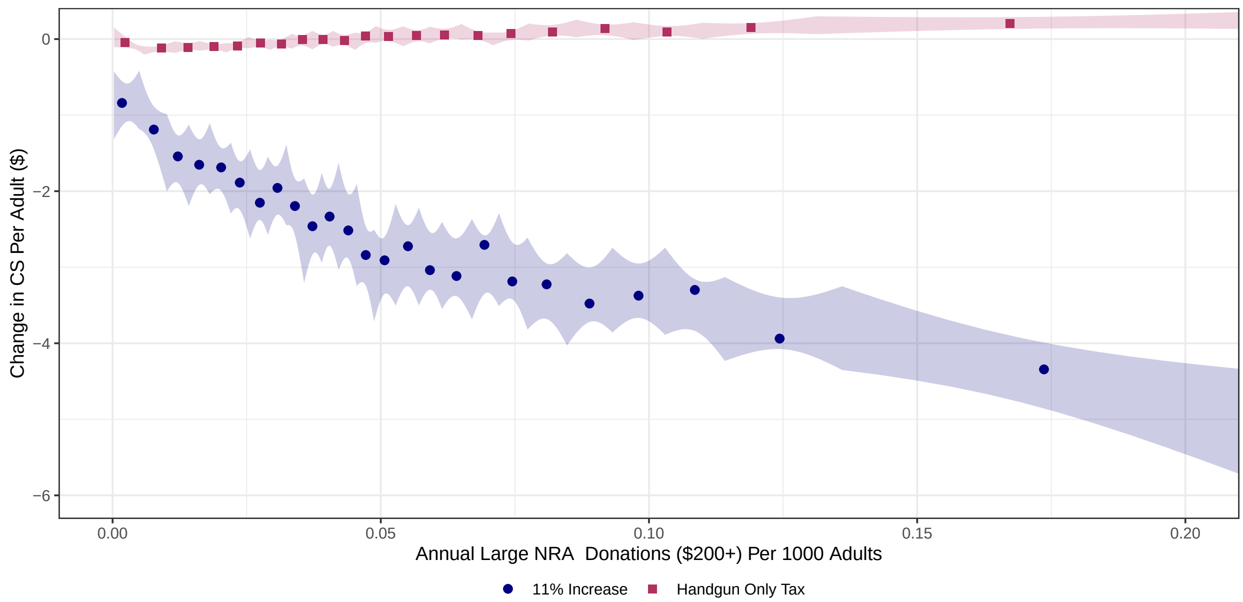


Figure OA.23: Effect of Tax Reforms on Consumer Surplus, by NRA Prominence (Donations Per Capita)

Figure shows a binscatter of the change in consumer surplus estimates at the congressional district level plotted against donations per capita. Bins are chosen via the data-driven procedure of Cattaneo et al. (2019).